Multi-Level Modeling of Complex Socio-Technical Systems – Phase 1

Final Technical Report SERC-2013-TR-020-2

June 6, 2013

Principal Investigator: Dr. William B. Rouse, Stevens Institute of Technology

Co-Principal Investigator: Dr. Douglas A. Bodner, Georgia Institute of Technology

Contract Number: H98230-08-D-0171

TO 0029, RT 044a

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
6 JUN 2013	**Final**	

4. TITLE AND SUBTITLE **Multi-Level Modeling of Complex Socio-Technical Systems - Phase 1**	5a. CONTRACT NUMBER **H98230-08-D-0171**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) **Rouse /Dr. William B.**	5d. PROJECT NUMBER **RT 44-2**
	5e. TASK NUMBER **TO 0029**
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Stevens Institute of Technology Georgia Institute of Technology**	8. PERFORMING ORGANIZATION REPORT NUMBER **SERC-2013-TR-020-2**
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) **DASD (SE)**	10. SPONSOR/MONITOR'S ACRONYM(S)
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release, distribution unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
This report presents a conceptual framework for multi-level modeling of complex socio-technical systems, provides linkages to the historical roots and technical underpinnings of this framework, and outlines a catalog of component models for populating multi-level models. This includes a description of the "systems movement," a summary of philosophical underpinnings, a review of seminal concepts, an overview of complex systems, discussion of complex adaptive systems, and contrasts of a range of systems approaches. Alternative modeling frameworks, including multi-level modeling frameworks, problem structuring methods, and computational representations, are also addressed. A proposed framework is presented for multi-level modeling of socio-technical systems, including discussion of the phenomena typically associated with each level, as well as a wide range of models of human behavior and performance. A comparison is provided of multi-level representations of the domains of healthcare delivery, energy consumption, and military operations. An illustrative example is presented focused on counterfeit parts in the military supply chain, in terms of both the consequences of such parts and interdicting the motivations to counterfeit. Finally, a wide range of fundamental research issues underlying multi-level modeling of complex systems is summarized.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**UU**	**66**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

This material is based upon work supported, in whole or in part, by the U.S. Department of Defense through the Systems Engineering Research Center (SERC) under Contract H98230-08-D-0171. SERC is a federally funded University Affiliated Research Center managed by Stevens Institute of Technology

The authors gratefully acknowledge the helpful comments and suggestions of John Casti and Harold Sorenson

ABSTRACT

This report presents a conceptual framework for multi-level modeling of complex socio-technical systems, provides linkages to the historical roots and technical underpinnings of this framework, and outlines a catalog of component models for populating multi-level models. This includes a description of the "systems movement," a summary of philosophical underpinnings, a review of seminal concepts, an overview of complex systems, discussion of complex adaptive systems, and contrasts of a range of systems approaches. Alternative modeling frameworks, including multi-level modeling frameworks, problem structuring methods, and computational representations, are also addressed. A proposed framework is presented for multi-level modeling of socio-technical systems, including discussion of the phenomena typically associated with each level, as well as a wide range of models of human behavior and performance. A comparison is provided of multi-level representations of the domains of healthcare delivery, energy consumption, and military operations. An illustrative example is presented focused on counterfeit parts in the military supply chain, in terms of both the consequences of such parts and interdicting the motivations to counterfeit. Finally, a wide range of fundamental research issues underlying multi-level modeling of complex systems is summarized.

Keywords: Multi-level models, socio-technical systems, complex systems, complexity, models of human behaviors and performance, decision making

This Page Intentionally Left Blank

TABLE OF CONTENTS

FIGURES AND TABLES

1.0 INTRODUCTION

Socio-technical systems involve behavioral and social aspects of people and society that interact with technical aspects of organizational structure and processes -- both engineered and natural -- to create organizational outcomes and overall system performance. These types of systems are often characterized as complex adaptive systems where independent agents pursue their individual objectives while learning and adapting to evolving system structures and behaviors.

Such systems can be described at various levels of abstraction and aggregation. Levels of abstraction might vary from individual human activities, to processes that support activities, to organizations that invest in and maintain processes, to social systems that create and regulate the policy environment in which organizations operate. Levels of aggregation could range, for example, from individual humans, to cohorts of similar humans (e.g., those with high risk of diabetes), to broader classes of humans (e.g., economic classes), to entire populations (e.g., countries' populations).

The appropriate level at which to represent socio-technical systems depends on the questions or problems being addressed. In other words, the choice of levels should be based on the utility of the representation for addressing the issues at hand, rather than the notion of their being a one, true "correct" representation. Further, it is quite possible that the issues of interest will dictate representing the system at multiple points in the abstraction-aggregation space. For example, one might need low abstraction, low aggregation representation of individual patients and their chronic diseases, as well as a high abstraction, high aggregation representation of the evolution of the inflation rate for the costs of healthcare. One complication here is that not all questions or problems may be known at the time of model conception, since stakeholders may develop new questions during the course of the model lifecycle.

Thus, multi-level representations are often needed to capture the phenomena associated with the question or problem of interest. This need often reflects both the "physics" of the phenomena of interest and the "psychics" of the solution development and deployment. More specifically, the behavioral and social nature of stakeholders' involvement with the evolution of a solution often requires some way for technically less sophisticated stakeholders to obtain a deep appreciation for the phenomena under study. Such appreciation is often a prerequisite to these stakeholders committing to deploy a solution. Multi-level models, with rich interactive visualization capabilities can provide a means to achieve these ends.

The ideas summarized in the preceding paragraphs have been germinating and evolving for many decades. Many people and disciplines have contributed to a large knowledge base underpinning these ideas. The primary goal of this report is to present and summarize this body of knowledge; a secondary but also important goal is to illustrate the practical implications of drawing upon specific elements of this body of knowledge to address a particular problem. These goals are addressed as follows.

Section 2 provides background for later sections. It includes a description of the "systems movement," a summary of philosophical underpinnings, a review of seminal concepts, an overview of complex systems, discussion of complex adaptive systems, and contrasts of a range of systems approaches. Section 3 focuses on alternative modeling frameworks, including multi-level modeling frameworks, problem structuring methods, and computational representations.

Section 4 outlines a proposed framework for multi-level modeling of socio-technical systems, including discussion of phenomena typically associated with each level, as well as a wide range of models of human behavior and performance. Section 5 gives a comparison of multi-level representations of the domains of healthcare delivery, energy consumption, and military operations. Section 6 presents a detailed example focused on the appearance of counterfeit parts in the military supply chain, addressing both the consequences of such parts in the supply chain and ways for interdicting the temptations to counterfeit.

Section 7 summarizes a wide range of fundamental research issues underlying multi-level modeling of complex systems. Section 8 summarizes the findings and implications of this report. A comprehensive list of references is provided at the end of this report.

The overarching objective of this report is to provide a rigorous foundation for multi-level modeling to support decision making in complex socio-technical systems. These models are envisioned as being created to support explorations of answers to decision makers' questions, ranging from strategic investments to system design and development to operation and maintenance of complex systems. Targeted domains include military operations, urban resilience, energy consumption and healthcare delivery.

2.0 BACKGROUND

2.1 SYSTEMS MOVEMENT

The systems movement emerged from the formalization of systems theory as an area of study during and following World War II, although it can be argued that the physicists and chemists of the 19th Century contributed to the foundations of this area. Before delving into the ideas emerging in the 1940s and beyond, it is important to distinguish four aspects of the systems movement:

Systems Thinking is the process of understanding how things influence one another within a whole and represents an approach to problem solving that views "problems" as components of an overall system

Systems Philosophy is the study of systems, with an emphasis on causality and design. The most fundamental property of any system is the arbitrary boundary that humans create to suit their own purposes

Systems Science is an interdisciplinary field that studies the nature of complex systems in nature and society, to develop interdisciplinary foundations, which are applicable in a variety of areas, such as engineering, biology, medicine and economics

Systems Engineering is an interdisciplinary field focused on identifying how complex engineering undertakings should be designed, developed and managed over their life cycles

Contrasting these four aspects of systems, it is important to recognize that different disciplines tend to see "systems" quite differently, for the most part due to the varying contexts of interest (Adams, et al., 2013). Thus, a systems scientist studying marsh ecosystems and a systems engineer designing and developing the next fighter aircraft will, from a practical perspective at least, have much less in common than the term "system" might lead one to expect. The key point is that systems exist in contexts and different contexts may (and do) involve quite disparate phenomena.

2.2 PHILOSOPHICAL BACKGROUND

There are many interpretations of what system thinking means and the nature of systems thinkers. Some are inclined towards model-based deduction, while others are oriented towards data-driven inference. The former extol the deductive powers of Newton and Einstein, while the latter are enamored with the inferential capabilities of Darwin. These different perspectives reflect different epistemologies.

The study of epistemology involves the questions of what is knowledge, how can it be acquired, and what can be known. The empiricism branch of epistemology emphasizes the value of experience. The idealism branch sees knowledge as innate. The rationalism branch relies on reason. The constructivism branch seeks knowledge in terms of creation. These branches differ in terms of how they represent knowledge, in particular how this knowledge is best modeled and simulated (Tolk, 2013).

There are many possible views of complexity and complex systems (Rouse, 2007). Systems paradigms for representation of knowledge include hierarchical mappings, state equations, nonlinear mechanisms, and autonomous agents (Rouse, 2003). For hierarchical mappings, complexity is typically due to large numbers of interacting elements. With uncertain state equations, complexity is due to large numbers of interacting state variables and significant levels of uncertainty. Discontinuous, nonlinear mechanisms attribute complexity to departures

from the expectations stemming from continuous, linear phenomena. Finally, autonomous agents generate complexity via the reactions of agents to each other's behavior and lead to emergent phenomena. The most appropriate choice among these representations depends on how the boundaries of the system of interest are defined (Robinson, et al., 2011).
Horst Rittel argued that the choice of representation is particularly difficult for "wicked problems" (Rittel & Webber, 1973). There is no definitive formulation of a wicked problem. Wicked problems have no stopping rule – there is always a better solution, e.g., "fair" taxation and "just" legal systems. Solutions to wicked problems are not true or false, but good or bad. There is no immediate nor ultimate test of a solution to a wicked problem. Wicked problems are not amenable to trial and error solutions. There is no innumerable (or an exhaustively describable) set of potential solutions and permissible operations. Every wicked problem is essentially unique. Every wicked problem can be considered a symptom of another problem. Discrepancies in representations can be explained in numerous ways – the choice of explanation determines the nature of problem's resolution. Problem solvers are liable for the consequences of the actions their solutions generate. Many real world problems have the above characteristics.

The notion of wicked problems raises the possibility of system paradoxes (Baldwin, et al., 2010). Classic paradoxes include whether light is a particle or a wave. Contemporary paradoxes include both collaborating and competing with the same organization. The conjunction paradox relates to the system including element A and element not A. The bi-conditional paradox holds if A implies B and B implies A. For the equivalence paradox, system elements have contradictory qualities. With the implication paradox, one or more system elements lead to its own contradiction. The disjunction paradox involves systems that are more than the sum of their parts. Finally, the perceptual paradox reflects perceptions of a system that are other than reality.

Finally, there are fundamental theoretical limits as to what we can know about a system and its properties (Rouse, 1986, 1989, 1991). There are limits of system information processing capabilities (Chaitin, 1974), limits to identifying signal processing and symbol processing models, limits of validating knowledge bases underlying intelligent systems, and limits of accessibility of mental models in terms of forms and content of representations. The implication is that models are inherently approximations of reality and may be biased and limited in significant ways.

2.3 Seminal Concepts

2.3.1 Systems Science

The experiences of the problem-driven research in World War II led many now-notable researchers to develop new concepts, principles, models, methods and tools for specific military problems that they later generalized to broader classes of phenomena. The systems

theorists included Norbert Weiner (1948) who generalized control theory into the concept of cybernetics. Weiner defined cybernetics as the study of control and communication in the animal and the machine. Studies in this area focus on understanding and defining the functions and processes of systems that have goals and that participate in circular, causal chains that move from action to sensing to comparison with desired goal, and back again to action. Concepts studied include, but are not limited to, learning, cognition, adaptation, emergence, communication, efficiency and effectiveness. Later extensions of control theory include optimal state filtering (Kalman, 1960) and optimal control (Bellman, 1957; Pontryagin, et al, 1962)
Claude Shannon (1948) developed information theory to address the engineering problem of the transmission of information over a noisy channel. The most important result of this theory is Shannon's coding theorem, which establishes that, on average, the number of bits needed to represent the result of an uncertain event is given by its entropy, where entropy is a measure of the uncertainty associated with a random variable. In the context of information theory, the term refers to Shannon entropy, which quantifies the expected value of the information contained in a message, typically measured in binary digits or bits. Shannon's noisy-channel coding theorem states that reliable communication is possible over noisy channels provided that the rate of communication is below a certain threshold, called the channel capacity. The channel capacity can be approached in practice by using appropriate encoding and decoding systems.

Ross Ashby (1951, 1956) added the Law of Requisite Variety to the canon. Put succinctly, only variety can destroy variety. More specifically, if a system is to be fully regulated, the number of states of its control mechanism must be greater than or equal to the number of states in the system being controlled. Thus, in order for an enterprise to reduce the variety manifested by its environment to yield less varied products and services, it must have sufficient variety in its business processes.

Bertalanffy (1968) developed General Systems Theory over several decades, with particular interest in biological and open systems, i.e., those that continuously interact with their environments. The areas of systems science that he included in his overall framework encompass cybernetics, theory of automata, control theory, information theory, set, graph and network theory, decision and game theory, modeling and simulation, and dynamical systems theory – in other words, virtually all of systems science. Bertalanffy includes consideration of systems technology including control technology, automation, computerization, and communications. Had the field of artificial intelligence existed in his time, that area would have surely been included as well. As is often the case with grand generalizations, it is often difficult to argue with the broad assertions but sometimes not easy to see the leverage gained.

Ackoff (1981) coined the term "system of systems" that has gained great currency of late. He recognized that organizations could be seen as systems. In this context, he outlined a classification of systems (self-maintaining, goal-seeking, multi-goal seeking, purposive system), and elaborated the notions of system state, system changes, and system outcomes, where outcomes are seen as the consequences of system responses, not just the response variables in themselves. He further elaborated organizational systems as being variety-increasing or variety-decreasing, and discusses adaptation and learning.

2.3.2 Economics/Cognition

It may seem odd to group economics with cognition. However, much seminal thinking arose from people who studied behavioral and social phenomena associated with economic processes. Nobel Prize winner Kenneth Arrow (1951, 1954) developed social choice theory, the associated impossibility theorem, equilibrium theory, and the economics of information. Nobel Prize winner Herbert Simon (1957, 1962) studied bounded rationality, satisficing vs. optimizing, behavioral complexity as a reflecting of environmental complexity, human information processing, and artificial intelligence. Nobel Prize winner Daniel Kahneman (2011), with his colleague Amos Tversky, studied human decision making biases and heuristics for several decades. Finally, George Miller (1956) contributed to cognitive psychology, cognitive science, and psycholinguistics (which links language and cognition), and studies of short-term memory – coming up with oft-cited "magic number seven."

This body of work provides important insights into socio-technical systems (as well as into how to win a Nobel Prize in Economics). Put simply, the classical notional of "economic man" as a completely rational, decision maker who can be counted on to make optimal choices is often a wildly idealistic assumption. The phenomena studied by Arrow, Simon, Kahneman and Miller make classical mathematical economics quite difficult. On the other hand, these phenomena can make agent-based simulations quite important. Later in this report, the modeling of human decision making is considered in some depth, with many concepts traceable back to the seminal thinkers discussed in this section.

2.3.3 Operations Research

Operations research emerged from World War II and efforts to look at military operations and improve them. Philip Morse was a pioneer in the research philosophy of immersing problem solvers in the complex domains where solutions are sought. The key element was the emphasis on research in operational contexts rather than just study of mathematical formalisms. Morse (1951, 1958) authored the first books in the United States in this area, and went on to publish an award-winning book on the application of OR to libraries (Morse, 1968).

C. West Churchman was internationally known for his pioneering work in operations research, system analysis and ethics. He was recognized for his then radical concept of incorporating ethical values into operating systems (Churchman, 1971). Ackoff received his doctorate in philosophy of science in 1947 as Churchman's first doctoral student (Ackoff & Churchman, 1957). He became one of the most important critics of the so-called "technique-dominated Operations Research", and proposed more participative approaches. He argued that any human-created system can be characterized as a "purposeful system" when it's "members are also purposeful individuals who intentionally and collectively formulate objectives and are parts of larger purposeful systems" (Ackoff & Emery, 1972).

More recently, Operations Research has come to be dominated by applied mathematics as an end in itself. The quest for provably optimal solutions of problems has resulted in problems being scaled down, often dramatically, to enable analytical proofs of optimality. The constructs of theorems and proofs have often displaced the intention to actually solve realistically complex problems. The value of immersing researchers in complex operational domains has often come to be discounted as impractical by the researchers themselves.

2.3.4 Sociology

Talcott Parsons was one of the first social scientists to become interested in systems approaches. He developed action theory, the principle of voluntarism, understanding of the motivation of social behavior, the nature of social evolution, and the concept of open systems (Parsons, 1937, 1951, 1956). This very much set the stage for the emergence of socio-technical systems as an area of study in its own right.

The idea of work systems and the socio-technical systems approach to work design was originated by Trist, Emery and colleagues (Trist & Bamforth, 1951; Emery & Trist, 1965, 1973). This included research on participative work design structures and self-managing teams. It also led to a deep appreciation of the roles of behavioral and social phenomena in organizational outcomes and performance.

2.4 Complex Systems

This section considers differing perspectives on the nature of complex systems; drawing upon several recently published review papers (Rouse, 2003, 2005, 2007; Rouse & Serban, 2011). It is useful to note that different disciplines, in part due to the contexts in which they work, can have significantly varying views of complexity and complex systems.

Several concepts are quite basic to understanding complex systems. One key concept is the dynamic response of a system as a function of structural and parametric properties of the system. The nature of the response of a system, as well as the stability and controllability of this response, is a central concern. Many operations research studies focus on steady-state behavior, while economics research addresses equilibrium behavior. However, transient behaviors – whether of the weather or the financial system – are often the most interesting and sometimes the most damaging.

Another basic concept is uncertainty about a system's state. The state of a system is the quantities/properties of the system whose knowledge, along with future inputs, enables prediction of future values of this set of variables. Uncertainty of system state limits the effectiveness of control strategies in assuring system performance. State estimation – filtering, smoothing and prediction – is an important mechanism for obtaining the best information for controlling a complex system. Related topics include the value of information and performance risks, e.g., consequences of poor performance.

It is useful differentiate the notions of "system" and "complex system" (Rouse, 2003). A system is a group or combination of interrelated, interdependent, or interacting elements that form a collective entity. Elements may include physical, behavioral, or symbolic entities. Elements may interact physically, computationally, and/or by exchange of information. Systems tend to have goals/purposes, although in some cases the observer ascribes such purposes to the system from the outside so to speak.

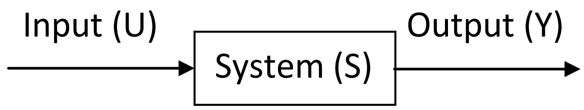
Note that a control system could be argued to have elements that interact computationally in terms of feedback control laws, although, one might also argue that the interaction takes place in terms of the information that embodies the control laws. One could also describe the control function in terms of physical entities such as voltages and displacements. Thus, there are (at least) three different representations of the same functionality -- hence, the "and/or" in the definition.

A complex system is one whose <u>perceived</u> complicated behaviors can be attributed to one or more of the following characteristics: large numbers of elements, large numbers of relationships among elements, nonlinear and discontinuous relationships, and uncertain characteristics of elements and relationships. From a functional perspective, the presence of complicated behaviors, independent of underlying structural features, may be sufficient to judge a system to be complex. Complexity is perceived because apparent complexity can decrease with learning.

More specifically, system complexity tends to increase with the number of elements, number of relationships, nature of relationships (i.e., logical: AND vs. OR & NAND; functional: linear vs. nonlinear; spatial: lumped vs. distributed; structural: for example, feed forward vs. feedback; response: static vs. dynamic; time constant: (not too) fast vs. (very) slow, and uncertainty: known properties vs. unknown properties, and knowledge, experience and skills (relative to all of the above, relative to observer's intentions).

The issue of intentions is summarized in Figure 1 (Rouse, 2007). If one's intention is simply to classify as observed object as an airplane, the object is not particularly complex. If one wanted to explain why it is an airplane, the complexity of an explanation would certainly be greater than that of a classification. For these two intentions, one is simply describing an observed object.

Complexity – f (Intentions)



Intention	Example
Classification	"It's an instance of type S."
Explanation	"It's type S because …"
Prediction	"Its future output will be Y."
Control	"If input is U, its output will be Y."
Detection	"Its output is not Y, but should be."
Diagnosis	"Its output is not Y because …"

Figure 1. Relationship of Complexity and Intentions

If one's intention is to predict the future state of the airplane, complexity increases substantially as one would have to understand the dynamic nature of the object, at least at a functional level but perhaps also at a structural level. Control requires a higher level of knowledge and skill concerning input-output relationships. Intentions related to detection and diagnosis require an even greater level of knowledge and skill concerning normal and off-normal behaviors in terms of symptoms, patterns, and structural characteristics of system relationships. The overall conclusion is that the complexity of a system cannot be addressed without considering the intentions associated with addressing the system.

The nature of human and social phenomena within a system has thus far not been considered. Systems where such phenomena play substantial roles are often considered to belong to a class of systems termed complex adaptive systems (Rouse, 2000, 2008). Systems of this type have the following characteristics:

- They tend to be **nonlinear, dynamic** and do not inherently reach fixed equilibrium points. The resulting system behaviors may appear to be random or chaotic.
- They are composed of **independent agents** whose behavior can be described as based on physical, psychological, or social rules, rather than being completely dictated by the physical dynamics of the system.
- Agents' needs or desires, reflected in their rules, are not homogeneous and, therefore, their **goals and behaviors are likely to differ or even conflict** -- these conflicts or competitions tend to lead agents to adapt to each other's behaviors.
- Agents are **intelligent and learn** as they experiment and gain experience, perhaps via "meta" rules, and consequently change behaviors. Thus, overall system properties inherently change over time.

- Adaptation and learning tends to result in **self-organization** and patterns of behavior that emerge rather than being designed into the system. The nature of such emergent behaviors may range from valuable innovations to unfortunate accidents.
- There is **no single point(s) of control** – system behaviors are often unpredictable and uncontrollable, and no one is "in charge." Consequently, the behaviors of complex adaptive systems usually can be influenced more than they can be controlled.

As might be expected, multi-level modeling of complex socio-technical systems having these characteristics creates significant complications. For example, the simulation of such models often does not yield the same results each time. Random variation may lead to varying "tipping points" among stakeholders for different simulation runs. These models can be useful in the exploration of leading indicators of the different tipping points and in assessing potential mitigations for undesirable outcomes. This topic is addressed in more detail later.

Snowden and Boone (2007) have argued that there are important distinctions that go beyond complex systems versus complex adaptive systems. Their Cynefin Framework includes simple, complicated, complex and chaotic systems. Simple systems can be addressed with best practices. Complicated systems are the realm of experts. Complex systems represent the domain of emergence. Finally, chaotic systems require rapid responses to stabilize potential negative consequences. The key distinction with regard to the types of contexts discussed in this report is complex versus complicated systems. There is a tendency, they contend, for experts in complicated systems to perceive that their expertise, methods and tools are much more applicable to complex systems than is generally warranted.

2.5 Systems Approaches

The evolution of systems practice has a rich history. During the 1900-1920s, Henry Gantt (1861-1919), Frederick Taylor (1856-1919), and Frank Gilbreth (1868-1924) pioneered scientific management. Quality assurance and quality control emerged in the 1920-30s, led by Walter Shewhart (1891-1967). Peter Drucker (1909-2005) and Chester Barnard (1886-1961) formalized corporate operations management in the 1940-50s. During and following World War II, Philip Morse (1903-1985), C. West Churchman (1913-2004), George Dantzig (1914-2005), and Russell Ackoff (1919-2009) were leading thinkers in operations research. Stafford Beer (1926-2002) articulated the foundations of management cybernetics in the 1960-70s. W. Edwards Deming (1900-1993) and Joseph Juran (1904-2008) brought total quality management to the U.S. in the 1970-80s. Michael Hammer (1948-2008) and James Champy led the wave of business process reengineering in the 1990s. Taiichi Ohno's (1912-1990) innovations in six sigma and lean production gained traction in the U.S. in the 1990-2000s. Most recently, Daniel Kahneman has led the way for behavioral economics in the 2010s.

Over more than a century, systems thinking tried to become increasingly rigorous, focusing on mathematics, statistics, and computation. During the 1960-70s, many thought leaders began to recognize that forcing all phenomena into this mold tended to result in many central phenomena being assumed away to allow for the much-sought theorems and proofs to be obtained. In particular, behavioral and social phenomena associated with complex systems were simplified by viewing humans as constrained but rational decision makers who always made choices that optimized the objective performance criteria (linear if lucky).

The reaction, particularly in the United Kingdom, to such obviously tenuous assumptions was the emergence of the notion of hard vs. soft systems thinking (Pidd, 2004). Table 1 contrasts these two points of view. Hard systems thinking seeks quantitative solutions of mathematical models that are assumed to be valid representations of the real world and, consequently, will inherently be embraced once they are calculated. Soft systems thinking sees modeling as a means for exploration and learning via intellectual and inherently approximate constructs open to discussion and debate.

Hard Systems Thinking	Soft Systems Thinking
Oriented to goal seeking	Oriented to learning
Assumes the world contains systems that can be "engineered"	Assumes the world is problematical but can be explored using models or purposeful activity
Assumes systems models to be models of the world	Assumes systems models to be intellectual constructs to help debate
Talks the language of problems and solutions	Talks the language of issues and accommodations
Philosophically positivistic	Philosophically phenomenological
Sociologically functionalist	Sociologically interpretative
Systematicity lies in the world	Systematicity lies in the process of inquiry into the world

Table 1. Hard vs Soft Systems Thinking (Pidd, 2004)

Table 2 contrasts systems approaches (Jackson, 2003). Hard systems thinking represents but one cell in this table. Other methods are much less "closed form" in orientation, relying more on simulation as well as participative mechanisms. The keys for these latter mechanisms are insights and consensus building.

		Participants		
		Unitary	**Pluralist**	**Coercive**
Systems	**Simple**	Hard Systems Thinking	Soft Systems Approaches	Emancipatory Systems Thinking
	Complex	System Dynamics Organizational Cybernetics Complexity Theory		Postmodern Systems Thinking

Table 2. Systems Approaches (Jackson, 2003)

Table 3 contrasts methodologies and problems (Jackson & Keys, 1984). Again, only one cell of the table includes traditional operations research and systems analysis. For other than mechanical problems with a single decision maker, much more participative approaches are warranted, at least if the goal is solving the problem of interest rather than just modeling the "physics" of the context.

	Mechanical	**Systemic**
Unitary – One Decision Maker	Operations Research Systems Engineering Systems Analysis	Organizational Cybernetics Socio-Technical Systems
Pluralist – Multiple Independent Decision Makers	Singerian Inquiry Systems Strategic Assumption Methods Wicked Problem Formulations	General Systems Theory Complex Adaptive Systems Soft Systems Methodology

Table 3. Methodologies vs. Problems (Jackson & Keys, 1984)

Table 4 summarizes Ulrich's (2008) levels of system practice. He differentiates hard versus soft in terms of three categories – one hard and two versions of soft. One class of soft management addresses change while the other addresses conflict. The key disciplines and tools vary substantially across these three categories.

Aspect	Operational Systems Management	Strategic Systems Management	Normative Systems Management
Dominating Interpretation	Systematic	Systemic	Critical Idea of Reason
Strand of Systems Thinking	Hard – Mechanistic Paradigm	Soft – Evolutionary Paradigm	Soft – Normative Paradigm
Dimension of Rationalization	Instrumental	Strategic	Communicative
Main Object of Rationalization	Resources – Means of Production	Policies – Steering Principles	Norms – Collective Preferences
Task of the Expert	Management of Scarceness	Management of Complexity	Management of Conflict
Type of Pressure	Costs	Change	Conflict
Basic Approach	Optimization	Steering Capacity	Consensus
Goodness Criterion	Efficient	Effective	Ethical
Theory-Practice Mediation	Decisionistic	Technocratic	Pragmatistic
Key Disciplines	Decision Theory, Economics, Engineering	Game Theory, Ecology, Social Sciences	Discourse Theory, Ethics, Critical Theory
Example Tools	Cost-Benefit Analysis, Linear Optimization	Sensitivity Analysis, Large-Scale Simulation	Systems Assessment, Ideal Planning
Trap to Avoid	Suboptimization	Social Technology	Excluding the Affected

Table 4. Levels of Systems Practice (Ulrich, 2008)

Table 5 summarizes Jackson's (2003) Critical Systems Practice. The most important aspect of his guidance is to remain open to the range of possibilities in Tables 1-4. From the perspective of multi-level modeling of complex systems, this means that the nature of the levels and how they are populated with component models should be driven by the issues of interest, the phenomena underlying these issues, and the orientations of the key stakeholders in the problem framing and solving processes.

Creativity	
Task	To highlight significant concerns, issues and problems
Tools	Creativity-enhancing devices employing multiple perspectives
Outcome	Dominant and dependent concerns, issues and problems
Choice	
Task	To choose an appropriate generic systems methodology
Tools	Methods for revealing methodological strengths and weaknesses
Outcome	Dominant and dependent generic systems methodologies
Implementation	
Task	To arrive at and implement specific positive change proposals
Tools	Generic systems methodologies
Outcome	Highly relevant and coordinated change yielding improvements
Reflection	
Task	To produce learning about the problem and solution
Tools	Clear understanding about the current state of knowledge
Outcome	Research findings that fed back into practice

Table 5. Critical Systems Practice (Jackson, 2003)

Pidd (2004) offers the notion of complementarity as a way of rationalizing the relationship between hard and soft approaches. He argues that hard and soft approaches are complementary to each other, but their complementarity is asymmetric. He asserts that any problem situation in human affairs will always at some level entail differences in world views that the "soft" approaches can be used to explore. Within that exploration, any or all of the hard approaches can be adopted as a conscious strategy. The reverse strategy is not available because it entails abandoning the ontological stance of hard approaches. In other words, hard approaches are often inextricably tied to paradigms and assumptions that are central to their problem solving power.

Gharajedaghi (2011) articulates a system methodology for supporting complex adaptive systems. The methodology focuses on functions, structure, and processes. To define functions, he argues that one should clarify which products solve which problems for which customers. To define structure, he advances the idea of a modular design that defines complementary relationships among relatively autonomous units. Finally, design of processes involves using a multidimensional modular design based on the triplet input (technology), output (products), and environments (markets).

This brief discussion of systems approaches serves to set the stage for alternative approaches to multi-level modeling of complex socio-technical systems. The nature of these systems usually precludes fully modeling them with first-principles physics models. Socio-technical systems are, by no means, as mechanistic and predictable as purely physical systems like bouncing balls or gear trains. Yet, there are well-developed approaches for addressing problem solving in complex socio-technical systems. Valid predictions, and occasionally optimization, are certainly of interest. However, insights into phenomena, sensitivities to key parameters, and consensus building are often the overarching goals.

3.0 ALTERNATIVE FRAMEWORKS

This report is focused on multi-level modeling of complex systems. The idea of representing systems at multiple levels of abstraction and aggregation is certainly far from novel (Rasmussen, 1986, 1994). Differing levels of abstraction enable representation of seemingly disparate phenomena, e.g., healthcare cost reimbursement policies versus impact of exercise on blood pressure levels. Differing levels of aggregation allow consideration of varying levels of detail, perhaps at each level of abstraction. Thus, an individual patient's blood pressure is important to predicting their risks of chronic diseases, but each person's consumption inclinations need not be considered to project growth of GDP and inflation.

Mihajlo Mesarovic and his colleagues (Mesarovic, et al., 1970) were pioneers in multi-level modeling of complex systems. Their conceptualization of the task of multi-level modeling is useful:

- "Selection of strata, in terms of which a given system is described, depends upon the observer, his knowledge and interest in the operation of the system, although for many systems, there are some strata that appear as natural or inherent." (p. 40)
- "Contexts in which the operation of a system on different strata is described are not, in general, mutually related; the principles or laws used to characterize the system on any stratum cannot generally be derived from the principles used on other strata." (p. 41)
- "There exists an asymmetrical interdependence between the functioning of a system on different strata." (p. 41) – any stratum depends on operations of lower strata
- "Each stratum has its own set of terms, concepts, and principles." (p. 41)
- "Understanding of a system increases by crossing the strata: in moving down the hierarchy, one obtains a more detailed explanation, while moving up in the hierarchy, one obtains a deeper understanding of its significance." (p. 42)

These observations are highly relevant to the exposition of multi-level models of complex systems provided in this report. The much more mathematical material in their treatise is restricted to two-level systems and assumes, at least implicitly, that the elements on each stratum have little if any discretion or, at the very least, that the objectives of each element (e.g., agent) are aligned with the overall system objectives. As discussed earlier, this assumption is often unwarranted for complex socio-technical systems.

In a very recent report, Mullen (2013) addresses the challenges of connecting legacy models, at one sitting on one computing platform, to meaningfully address new questions for which the component models were not inherently created to answer. It is much easier if models were designed to be composable. However, integration above the level of "plug and play" can still pose significant validity problems.

Zeigler (2000) addresses integration and coordination issues in multi-level modeling. He is concerned with differential equation, difference equation (discrete time) and discrete event representations. The focus is on how to computationally integrate these representations. Rationalizing and integrating differing time scales is a dominant issue. This is a necessary condition for meaningful multi-level modeling, but often not sufficient.
Resolution of timing issues will not achieve the highest levels of interoperability articulated by Tolk (2003):

- Level 4: Common Conceptual Model/Semantic Consistency
- Level 3: Common System Approach/Open Source Code
- Level 2: Use of Common Reference Models/Common Ontology
- Level 1: Documentation of Data and Interfaces
- Level 0: Isolated Systems

The difficulty of semantic integration is readily apparent when trying to integrate financial spreadsheets from disparate business units operating in different markets. However, this is easy compared to Mullen's challenge. Assuring semantic integration of simulation modules created decades apart and laced with undocumented assumptions is, some would argue, a fool's quest. Fortunately, once the "plug and play" requirement is relaxed and the use of arbitrarily chosen legacy components put aside, successful multi-level modeling is certainly possible.

3.1 Problem Structuring Methods

A central concern is appropriately defining the problem for which multi-level modeling is to be pursued. Mingers and Rosenhead (2003) contrast two broad classes of problems. Well-structured problems are those "for which a consensual formulation can be stated in terms of performance measure or measures, constraints and the relationship through which action produces consequences." Unstructured problems, by way of contrast, are those "characterized by the existence of multiple actors, multiple perspectives, incommensurable and/or conflicting interests, important intangibles, and key uncertainties."

These authors suggest requirements for good problem structuring methods:

- Enable several alternative perspectives to be brought into conjunction with each other
- Problem definitions should be cognitively accessible by actors with a range of backgrounds and without specialist training
- Operate iteratively, so that the problem representation can be adjusted to the state and stage of the discussion
- Permit partial or local improvements to be identified and committed to, rather than requiring a global solution

Mingers and Rosenhead then review fourteen methods and the extent to which they satisfy these requirements. The remainder of this section reviews three of them: Checkland's Soft Systems Methodology, Beer's Viable Systems Model, and Ulrich's Critical Systems Heuristics.
The Soft Systems Methodology (Checkland, 2003) includes seven steps. The first two focus on entering the problem situation and expressing it. Next, root definitions of relevant systems are formulated. Conceptual models of human activity systems are then constructed from the perspective of each stakeholder. These models are compared with the real world and used to define changes that are desirable and feasible. Finally, actions are taken to improve the real world situation.

Problem definition is central to success with this methodology. Checkland suggests the following guiding questions:

- Clients – Who are the beneficiaries or victims of this particular system?
- Actors – Who are responsible for implementing this system?
- Transformation – What transformation does this system bring about?
- Worldview – What particular worldview justifies the existence of this system?
- Owner – Who has the authority to change the system or its objectives?
- Constraints – Which external constraints does this system take as a given?

The Viable System Model (Beer, 1984) is premised on the notion that all organizational systems are composed of five component systems. Problem structuring concerns identifying how these five systems are functioning, or not functioning, within the context of interest. This overall model also provides guidance for designing functions that may not yet exist in this context.

- System 1 in a viable system contains several primary activities. Each System 1 primary activity is itself a viable system due to the recursive nature of systems as described above. These are concerned with performing a function that implements at least part of the key transformation of the organization.

- System 2 represents the information channels and bodies that allow the primary activities in System 1 to communicate between each other and which allow System 3 to monitor and co-ordinate the activities within System 1.
- System 3 represents the structures and controls that are put into place to establish the rules, resources, rights and responsibilities of System 1 and to provide an interface with Systems 4/5.
- System 4 includes the bodies that make up System 4 are responsible for looking outwards to the environment to monitor how the organization needs to adapt to remain viable.
- System 5 is responsible for policy decisions within the organization as a whole to balance demands from different parts of the organization and steer the organization as a whole.

Beer is, in effect, arguing for a standard multi-level model of complex organizational systems. His five models provide a template for problem structuring. The extent to which such standardization is meaningful across a wide range of contexts is discussed later.

Ulrich (2003) outlines several spheres of discourse. They range from local to multiple domains to public to societal. These domains tend to have differing stakeholders and varying interests. This argues for a multi-level representation of the overall phenomena of interest. His Critical Systems Heuristics (Ulrich, 2003; Jackson, 2003) include the following questions for guiding problem structuring:

- Who should to be the beneficiary of the system?
- What should to be the purpose of the system?
- What should to be the system's measure of success?
- Who should to be the decision maker?
- What elements of the system should the decision maker control?
- What resources and conditions should to be part of the system's environment?
- Who should to be involved as the designer of the system?
- What kind of expertise should contribute to the design of the system?
- Who should to be the guarantor of the system?
- Who should represent the concerns of those affected by the system?
- To what extent should those affected have chances of relief from impacts?
- What worldviews of those involved or affected should influence the design

3.2 Computational Representations

A computational formalism is a modeling formalism with a well-established computational implementation or implementations. Computational formalisms operate as structured languages for representing a system. As such, they enforce particular ways of representing phenomena that provide powerful means of representing certain phenomena, but also impose limitations in representing others. These are typically stand-alone means of representing systems and are traditional approaches to system modeling and analysis. Examples include the following.

- Queueing models study steady-state behavior of systems that have entities that engage in transactions with a set of resources (originating with Erlang's work on telecommunication systems). Traditional phenomena of interest include waiting times, throughput, queue lengths, etc. For the most part, queuing models are analytic and strongly dependent on assumptions with respect to probability distributions, etc. There are some computational approaches that relax these assumptions and use numerical methods.
- Discrete-event simulation was developed to study similar phenomena to queueing analysis, but without as many limiting assumptions. There are three major paradigms or worldviews for discrete-event simulation (Kiviat, 1967). The process-interaction paradigm, in particular, relies on a network-of-queues formalism. Event-scheduling, on the other hand, focuses primarily on events in terms of an event calendar whereby an initial event set executes, changing the system state and scheduling other events in the future. Activity-scanning focuses on activities and the necessary pre-conditions for activity initiation.
- Object-oriented simulation emerged with the shift to object-oriented programming as an alternative to representing systems as a network-of-queues. The idea was to develop class libraries of system components specialized to a particular domain of application (Zeigler, 1990).
- System dynamics was established to study complex and non-linear phenomena that result when system components affect one another in non-intuitive ways (Forrester, 1961). Flows between stocks and feedback loops are important concepts for representing system phenomena.
- Agent-based modeling was initiated to study emergent phenomena that results from the individual behavior of a networked set of actors (Holland, 1991).
- Optimization models seek to maximize or minimize an objective function subject to a constraint set. Algorithms to perform the optimization may either be exact or heuristic. Optimization lends itself to formal descriptions of system complexity.

Each of the above can be used to specify multi-level models, although the approach would typically be ad-hoc and dependent on characteristics of the system being modeled.
Computational formalisms proved to be poor methods for communicating models for a variety of reasons, including assumption documentation, stakeholder understanding, and model maintenance and reuse. Prose is not well-suited for these purposes either, due to its ambiguity and lack of formalism. Thus, interest developed in visual means to represent systems to serve as a bridge between prose and computational formalisms. One such formalism is the systemigram (Blair, Boardman & Sauser, 2007).

Fundamentally, systemigrams are a conceptual modeling approach using soft systems methodology. They are used to convert prose to a visual representation for purposes of communication, storyboarding and model understanding among stakeholders. The representation emphasizes concepts of emergence, hierarchy, boundaries and influence. Major applications include systems-of-systems and networked systems. Potentially, systemigrams could be used to represent multi-level systems and enterprises. One open issue is how to transit from a systemigram to a computational formalism. A potential area of research is the characterization of templates within the systemigram representation that could be used to derive models in a particular formalism, such as a queueing network or an optimization model.

Another visual formalism is the influence diagram, which provides a method for representing probabilistic events and decision events in a decision tree structure (Howard & Matheson, 2005). The main motivation here is to provide a visual means for model communication while maintaining a way to convert the representation to computational form. The influence diagram contains a sequence of time-step nodes that are formally represented via a combination of chance and decision nodes. Potentially multi-level phenomena can be represented, for example, by expanding a decision or chance node(s) into a more detailed sub-model.
Interest has continued to grow for visual modeling techniques that can be translated easily into computational models. Two visual formalisms, IDEF and UML in particular, have made a major impact on modeling.

IDEF began as a structured way to represent data about a system's or organization's inputs, decisions, actions and activities, independent of how that data was stored (Mayer et al., 1995). IDEF evolved into different generations of modeling techniques. IDEF began by enforcing a fundamentally process-oriented modeling perspective. But subsequent IDEF specifications address such concepts as time-varying system behavior, object-oriented perspectives and requirements capture. Each of these concepts lies within a particular specification, and there does not exist an integrated modeling framework that combines them. In addition, later specifications tend to be at the initial specification state. The set of specifications is shown in Table 6.

With the emergence of object-oriented programming, there was a need for methods to specify, design and document computer programs. A variety of methods were developed using visual techniques (Booch, 1991; Rumbaugh et al., 1990). Eventually, these coalesced into the Unified Modeling Language (UML) (Jacobson, Booch & Rumbaugh, 1999). UML enforces a fundamentally object-oriented modeling perspective using a set of diagrams for software system design and documentation. The two major types of diagrams are structure diagrams, which specify the components of the software system, and behavior diagrams, which specify the events that occur during execution. Interaction diagrams are a subset of behavior diagrams that specify flow and control. UML is a standard adopted and managed by the Object Management Group (OMG), and it is also recognized as a standard by the International Organization for Standardization (ISO).

Generation	Purpose
IDEF0	Function modeling
IDEF1	Information modeling
IDEF1X	Data modeling
IDEF2	Simulation modeling design
IDEF3	Process specification capture
IDEF4	Object-oriented design
IDEF5	Ontology description capture
IDEF6	Design rational capture
IDEF7	Information system auditing
IDEF8	User interface modeling
IDEF9	Business constraint discovery
IDEF10	Implementation architecture modeling
IDEF11	Information artifact modeling
IDEF12	Organization modeling
IDEF13	Three schema mapping design
IDEF14	Network design

Table 6. IDEF Versions

With the success of the UML standard for software systems, there emerged a strong interest in the systems engineering community to have a similar standard for systems design, analysis, verification and validation, especially given the wide array of models and data representations used in these various phases of the system lifecycle. The goal was to provide a standard language to support the emerging field of model-based systems engineering (MBSE), as well as a set of resources for using the standard.
The OMG commissioned specification of SysML as an extension of UML to support systems engineering (Friedenthal, Moore & Steiner, 2008). This was conducted by a community-based effort involving many individuals and organizations, and it resulted in a standard for SysML adopted by OMG.

SysML supports both object modeling and process modeling. Both types of models, and their integration, are important to multi-level, enterprise modeling. SysML provides a number of diagram types to support the notion of modeling enterprises as systems. Diagram types include:

- Structure diagrams
  - Block definition diagrams to model system structure
  - Internal block diagram to represent interfaces and interconnections within a block
- Behavior diagrams
  - Activity diagrams to model state-based behavior from the perspective of inputs, outputs and controls
  - Sequence diagrams to model sequences of events/messages involving different system elements
  - State machine diagrams to model behavior of a system entity from the perspective of state changes caused by events
  - Use case diagrams to represent users interacting with a system and desired outcomes
- Requirements diagrams to model requirements and relationships between them and other system elements
- Parametric diagrams to represent constraints on system parameter values
- Package diagrams to organize various model elements (similar to UML)

SysML can be specialized into different system domains, such as enterprises-as-systems. As an extension of UML, it can provide a basis for software design (but this is limited since many SysML elements are not found in UML). Finally, SysML supports the notion of multi-level modeling via its structural and behavioral diagrams. SysML has been used to characterize organizational and enterprise structure and behavior for purposes of knowledge capture, sharing and reuse (McGinnis & Thiers, 2012).

While SysML has many obvious advantages for multi-level modeling, it has limitations especially in application to socio-technical systems. SysML typically is used to represent the technical aspects of systems. The main exception to this is the use-case diagram, used to represent stakeholder use of the system to meet goals. Behavioral and social phenomena can be represented in a technical sense via state-machine diagrams and such, but it is not clear to what extent this is adequate. It is also not clear whether SysML provides much support for conflict identification and resolution among requirements from a diverse set of stakeholders. This is a critical need in enterprise modeling.

A variety of tools exist to support SysML diagram specification. One goal of the MBSE community is to use SysML as a specification for data model repositories that support population of different analysis models for specific analyses. This is an active area of research.

With the limitations of single-formalism modeling approaches, there has been significant interest in combining different modeling paradigms within one formalism or technique. One approach that seeks to combine two formalisms is the work of Kim et al. (2003) in combining IDEF and UML. They target the domain of enterprise information technology systems, which are increasingly ubiquitous. These systems integrate many functions and have stakeholders with different perspectives. There is no modeling methodology or language that supports the entire scope of designing and developing such systems. Their paper explores whether different existing tools can be leveraged to provide a more useful and powerful approach to designing and developing enterprise IT systems.

In particular, IDEF appeals to "enterprise modelers," who are engineers who design business processes and engineer IT architectures to support them. UML, on the other hand, appeals to "distributed object system modelers," who design and develop software. This work is useful because it demonstrates how data elements in different IDEF representations can be mapped and made consistent with data elements in various UML representations, as well as leveraging prior work and communities of interest.

In terms of application to multi-level modeling of socio-technical systems, the following questions are relevant.

- Can this approach be generalized beyond IT systems to enterprises in general? In this case, would SysML be a more relevant choice than UML? Kim and colleagues mentions other methods/languages such as UEML and CIMOSA. Would these be relevant?
- How would this be operationalized in modeling tools?
- What would be involved in scaling this up if other methods/languages are needed?

The idea of multi-paradigm approaches and toolsets is driving much of the current effort in model-based systems engineering, since the broad goal is to support system design, development and testing via software models before and/or concurrently with those same processes using physical articles. Such a multi-paradigm approach is needed to support these different functional activities in the lifecycle. A variety of MBSE techniques are supported by software tools vendors and are in practice in a variety of domains, ranging from automotive to aerospace. Little (2009) describes a vision for MBSE using such tools, as well as extensive application types.

One critical, emerging technology to support this vision is that of model transformation (Czarnecki & Helsen, 2006). In general, model transformation is the concept that a model is input into a procedure that outputs a new type of model. Model transformation is a concept from the OMG's Model-Driven Architecture.
Here, it is specifically the concept that a descriptive model of a system (e.g., in SysML) can be used to generate a model for analysis using a particular computational formalism (e.g., simulation or optimization). In practice, a domain-specific model using a SysML stereotype is used as input to the transformation, which then outputs the structure of the analysis model within its formalism, as well as populates the analysis model with data (Batarseh & McGinnis, 2012). Model transformation is an emerging field of research that is increasingly important in MBSE.

One of the appealing features of model transformation is that a single, standard, visual modeling technique such as SysML can be used to store the system model, thus serving as the communication and model management medium. Typically, SysML is specialized for the domain under consideration for this purpose. The specific analysis models are generated automatically using a transformation technology, alleviating the need to manage multiple independent models across many different analysis paradigms.

Model transformation is in the early stages of maturity. However, given the potential multiple analysis model formalisms that may be used within a multi-level model, it could be of potential use in model and data management.

3.3 SUMMARY

This section has summarized a wide range of material including a description of the "systems movement," a summary of philosophical underpinnings, a review of seminal concepts, an overview of complex systems, discussion of complex adaptive systems, and the contrasts among a range of systems approaches. This material provides the building blocks for formulating an integrated approach to multi-level modeling of socio-technical systems. The "mortar" between these building blocks will be seen to be the ways in which human behavioral and social phenomena are incorporated into the overall framework.

4.0 PROPOSED FRAMEWORK

Design and evaluation of complex socio-technical systems can be addressed using the multi-level modeling framework shown in Figure 2. This framework explicitly represents the different levels of abstraction underlying system behaviors and performance. Note that this framework is a derivative of the ideas of Mesarovic, Rasmussen, Gharajedaghi, Beer and Ulrich discussed in earlier sections.

The levels of the framework can embody a range of phenomena, including engineered, organizational, and natural phenomena. Of particular importance to socio-technical systems are human behavioral and social phenomena. The remainder of this section focuses on such phenomena. The "physics" elements of multi-level models are doubtlessly important, but there are many sources on modeling such aspects of systems. Hence, this section focuses on the "human" elements of multi-level models.

People can only execute work practices at the lowest level of Figure 2. Work practices are supported by delivery operations in the next level, which only exist if the organizations within the system structure invest in and sustain these capacities, which they will only do if the domain ecosystem incentivizes and rewards the outcomes of these investments.

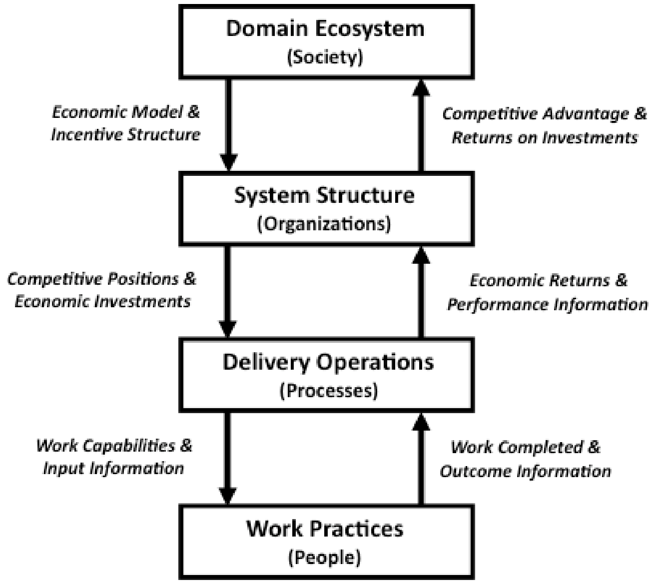


Figure 2. Multi-Level Modeling Framework

The domain ecosystem – society – defines the objectives for the system and the rules of the game. This includes explicit or implicit specification of what matters, what can and cannot be done, and how performance is rewarded. These specifications incentivize or impede organizational decisions.

These decisions include the nature of the system capacities considered, levels of investment in these capacities, and assessment of subsequent performance. In this way, delivery operations are created and sustained. They also may be impeded as, for example, by government price controls that can lead to disinvestment in capacities.

Delivery operations provide capacities for work. These capacities can include engineered systems (e.g., networks and databases, devices and platforms), processes (e.g., procedures, plans), and venues (e.g., factories, playing fields). Work practices or activities, at the bottom of Figure 2, can include physical manipulation (e.g., lifting, carrying, controlling), information provision (e.g., informing, advising) or social interaction (e.g., talking, performing).

The four levels in Figure 2 represent different levels of abstraction. Within each level, there can also be levels of aggregation, as illustrated by Figure 3. For example, individuals, teams, specialties (e.g., electricians) or whole workforces can perform work. Processes can be specific sets of steps, generic sequences of functions, or composite procedures for all automobiles or patients. Organizations can be departments, divisions, subsidiaries or whole corporations. The "grain sizes" of the networks at each level reflect the level of aggregation of the representation of the phenomena at that level.

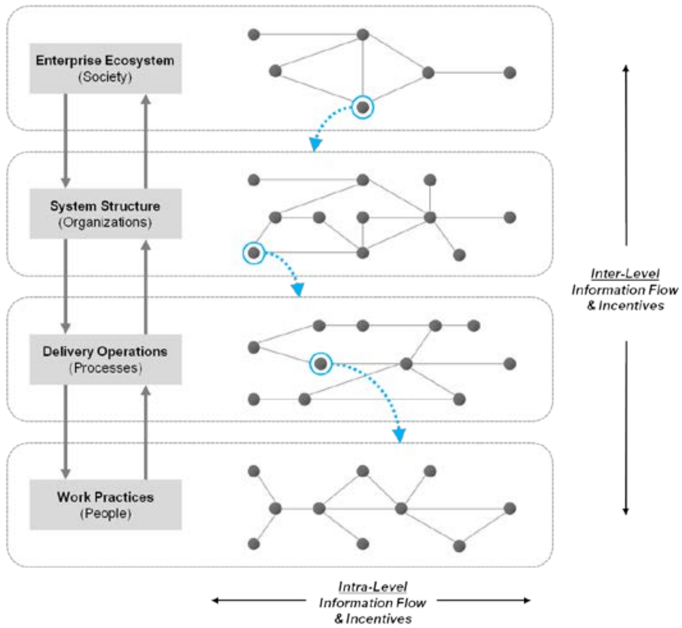


Figure 3. Networks of Phenomena at Each Level

It is important to note that Figures 2 and 3 are simplifications for the sake of exposition. Level-skipping relationships are not depicted. Feedback relationships, that are often pervasive, are also not shown. Finally, "field" types of relationships -- e.g., gravity, culture -- are also not depicted. Thus, a multi-level model of a realistically complex system can be quite a bit messier than Figures 2 and 3 might lead one to imagine.

4.1 Phenomena & Models

There can be a range of socio-technical phenomena represented in Figures 2 and 3. At the People level, the phenomena of interest are usually human behavior and performance -- individually, in teams, or in groups. Models at this level often involve input-output relationships in task activities with the focus on how well people perform. Not surprisingly, performance can be better predicted in tasks where humans have little discretion. For example, performance in landing as aircraft is more predictable than performance in troubleshooting an electronic circuit, which is more predictable than responding to a novel emergency.

For the Process level, human decisions concern allocating attention to the capabilities and information needed for task performance, including capabilities and information from other people. In this regard, a central socio-technical phenomenon are the social networks that enable processes. Of course, what people choose to attend to depends on the choices available. In some cases, a default alternative is to ignore the choices altogether, either intentionally or unintentionally.

The Organization level is typically concerned with economic decision making, drawing upon classical microeconomics or, more recently, behavioral economics. The key decisions here include allocating resources to processes and assessing the current and projected performance of processes. These decisions determine what choices and capacities are available at the process level.

At the Ecosystem level, policy decisions are made regarding what criteria and constraints apply to achieve overall objectives, both explicit and implicit, drawing upon macroeconomics and policy sciences. These policies tend to incentivize or inhibit decisions at the organization level. Thus, process decisions that are illegal or poor investments are unlikely to be made. For example, if Medicare will not pay for a particular procedure, healthcare providers are unlikely to invest in providing it.

Another example of socio-technical phenomena at the ecosystem level would seem to be the evolution of social and cultural norms and beliefs (Proctor, Nof & Yih, 2012). However, these phenomena tend to pervade all levels and, as noted above, may be best represented as "fields," similar to gravity, which affect the parameters at all other levels. For example, social systems that are more risk averse would have utility functions across levels with different parameters than social systems where risk is less of a concern.

There is a rich set of mathematical and computational models that can be drawn upon to represent the range of phenomena outlined above. Table 7 summarizes a range of alternatives. Development of a multi-level model involves choosing from these and other classes of representation, creating instantiations particular to the phenomena of interest, and parameterizing these instantiations based on data from the domains of interest. Thus, understanding the possible choices in Table 7 is very much a first step in formulating multi-level models. Instantiation and parameterization involve difficult work that seldom can be fully automated, especially if one is concerned with Tolk's semantic interoperability.

As discussed earlier, translating representations to computational forms is, of course, a critical step to developing multi-level models of complex socio-technical systems. For dynamic systems, this involves defining stocks, flows, feedback, control, and error measures; choosing differential or difference equations, depending on whether there are continuous states, or discrete transitions; and deciding how to compute transient responses and measures of stability. For discrete-event systems, this involves defining capacities, flows, queues, resource allocations, and the way time is addressed; choosing arrival and service processes (e.g., Poisson, exponential) and possibly characterizing Markov chains with discrete states and continuous transitions; as well as deciding how to compute steady-state responses. For agent-based systems, one must define the rules for information access and sampling, decision making, and adaptation; choosing the "grain size" of agents (e.g., individual patients versus cohorts of patients); and deciding how potential emergent behaviors will be recognized. For situations where optimization makes sense, this can include optimal feedback controls (e.g., error vs.

energy) and optimal allocations of resources (e.g., capacities, resource routes, schedules, inventory).

Level	Issues	Models
Society	GDP, Supply/Demand, Policy	Macroeconomic
	Economic Cycles	System Dynamics
	Intra-Firm Relations, Competition	Network Models
Organizations	Profit Maximization	Microeconomic
	Competition	Game Theory
	Investment	DCF, Options
Processes	People, Material Flow	Discrete-Event Models
	Process Efficiency	Learning Models
	Workflow	Network Models
People	Consumer Behavior	Agent-Based Models
	Risk Aversion	Utility Models
	Perception Progression	Markov, Bayes Models

Table 7. Levels of Modeling (Basole, et al., 2011)

Much of the above involves modeling and representation of the “physics” of the environment, infrastructure, vehicles, etc. These are certainly important elements of the overall multi-level model. However, the greatest challenge in developing such models in the modeling and representation of the behavioral and social behaviors and performance throughout the system, especially when it cannot be assumed that the human elements of the systems will behave in accordance with the objectives and “rules of engagement” of the overall system.

4.2 Human Behavior & Performance Modeling

To compile the possible approaches to modeling human behavioral and social phenomena at the various levels of Figures 2 and 3, the tasks of humans at these levels must first be defined. Table 8 provides a summary of these tasks. All four levels include both strategic and operational tasks, as well as detection, diagnosis and compensation tasks.

At the Ecosystem level, the key strategic task is to set the "rules of the game" for all levels. The operational task is to monitor organizational outcomes. The purpose of this monitoring is to detect anomalous organizational outcomes, diagnose the causes of these anomalies, and decide upon appropriate compensation schemes. All of these tasks are likely to be performed both individually and in groups. Input-output models for such tasks are described below.

The Organization level's strategic task is to allocate resources to processes so as to optimize outcomes within the rules of the game. The operational task is to monitor process outcomes. The purpose of this monitoring is to detect anomalous process outcomes, diagnose the causes of these anomalies, and decide upon appropriate compensation schemes. All of these tasks are likely to be performed both individually and in groups. Input-output models for such tasks are described below.

The strategic task at the Process level is to allocate process resources to enable work. The operational task is to monitor work outcomes in terms of performance. The purpose of this monitoring is to detect anomalous work outcomes, diagnose the causes of these anomalies, and decide upon appropriate compensation schemes. All of these tasks are more likely to be performed individually but may also be performed by groups or, more likely, teams. Input-output models for such tasks are described below.

The strategic task at the People level is to employ process resources to perform work. The operational task is to monitor work outcomes in terms of behaviors. The purpose of this monitoring is to detect anomalous work behaviors, diagnose the causes of these anomalies, and decide upon appropriate compensation schemes. All of these tasks are more likely to be performed individually but may also be performed by groups or, more likely, teams. Input-output models for such tasks are described below.

The concern at this point is how to populate multi-level models with alternative input-output relationships for the twenty cells of Table 8 for different contexts, e.g., piloting an aircraft versus managing a factory versus delivering healthcare. Fortunately, there is a rich knowledge base to draw upon, including National Academy studies in 1998 and 2008; frameworks by Sheridan (1974, 1992), Rouse (1980, 1983, 2007) and Rasmussen (1986, 1994); and computational models of social systems (Carley, 2002, 2009).

Pew and Mavor's National Academy study (1998) reviewed models of human behavior and performance in terms of attention and multi-tasking, memory and learning, human decision making, situation awareness, planning and behavior moderators, as well as integrative architectures. They acknowledged the richness of this knowledge base, but also questioned the maturity of the knowledge relative to the recognized modeling needs. One can argue, however, that modeling policy decision makers behaviors by starting with how they visually read characters on printed pages will be more overwhelming than useful.

Enterprise Level	Human Tasks				
	Strategic Task	**Operational Task**	**Detection Task**	**Diagnosis Task**	**Compensation Task**
Ecosystem	Set Rules of Game	Monitor Organization Outcomes	Detect Outcome Anomalies	Diagnose Causes of Anomalies	Compensate for Anomalous Outcomes
Organization	Allocate Process Resources	Monitor Process Outcomes	Detect Outcome Anomalies	Diagnose Causes of Anomalies	Compensate for Anomalous Outcomes
Process	Enable Work With Resources	Monitor Work Outcome (Performance)	Detect Outcome Anomalies	Diagnose Causes of Anomalies	Compensate for Anomalous Outcomes
People	Perform Work With Resources	Monitor Work Activities (Behavior)	Detect Outcome Anomalies	Diagnose Causes of Anomalies	Compensate for Anomalous Outcomes

Table 8. Human Tasks vs. Enterprise Level

More recently, Zacharias and his colleagues' National Academy study (2008) considered differ levels of models, including verbal conceptual models, cultural modeling, macro-level formal models (e.g., systems dynamics models and organizational modeling), meso-level formal models (e.g., voting and social choice models, social network models and agent-based modeling), micro-level formal models(e.g., cognitive architectures, expert systems and decision theory and game theory, and interactive games. This range of modeling methods and tools is much more relevant to the phenomena discussed in this report relative to the earlier Academy study.

Sheridan and Ferrell's (1974) classic on human-machine systems addresses modeling of a wide range of human behavior and performance. Humans' abilities to deal with uncertainty are characterized in terms of probability estimation, Bayesian probability revision, information measurement and channels, information transmission tasks, and continuous information channels. They provide an in-depth review of manual control performance including servomechanism models, input-output identification in time and frequency domains, and optimal control models. They summarize human characteristics in terms of sensory and neuromuscular abilities, as well as intermittent and nonlinear characteristics. Human decision making and utility, decisions under risk, signal detection, dynamic decision making, and formal games are discussed. The knowledge base in this classic is quite rich, although it is mostly focused on individual behavior and performance.

Sheridan (1992) addresses supervisory control where humans interact with complex systems via computers rather than directly, which is quite common in most systems now. He outlines the generic supervisory control functions of planning, teaching the computer, monitoring automatic control, intervening to update instructions or assume direct control, and learning from experience. He discusses extensions of manual, as opposed to automatic, control theory beyond his earlier treatment. He reviews contemporary results on human attention allocation models, fuzzy logic models, and cognition and mental models. He concludes by discussing limiting factors – free will, ambiguity, and complexity – that make prediction of human behavior and performance challenging.

Rouse (1980) presents a wide range of systems engineering models of human-machine interaction. Estimation theory models for state estimation, parameter estimation and failure detection are discussed. Control theory models for manual control; quickening, prediction and preview displays; and supervisory control are reviewed. Queuing theory models of visual sampling, monitoring behavior, and attention allocation are illustrated. Fuzzy set theory models for process control and fault diagnosis are discussed. Finally, artificial intelligence models are presented in terms of production systems, pattern recognition, Markov chains, and planning models. Overall, he shows how the "hard" methods of system dynamics and control, as well as operations research, can be applied to modeling human behavior and performance.

Rouse (1983) summarizes a wide range of models of human problem solving in the tasks of failure detection, failure diagnosis and failure compensation – note the relevance to the tasks in Table 8. He reviews eight mathematical models of failure detection and eleven mathematical models of failure diagnosis. The key conclusion is that there is a rich base of computational models to draw upon for modeling human behavior and performance for the detection and diagnosis tasks in Table 8.

Drawing upon a wide range of sources (Rasmussen & Rouse, 1981), Rouse presents a general three-level representation of human problem solving. Rasmussen's distinctions among skill-based, rule-based, and knowledge-based behaviors (Rasmussen, 1981), in combination with Newell and Simon's (1972) theory of human problem solving, led to the conclusion that problem solving occurs on more than one level – see Table 9.

When humans encounter a decision making or problem solving situation, they first consider available information on the state of the system. If this information maps to a familiar pattern, whether normal or abnormal, they perhaps unconsciously invoke a frame (Minsky, 1975) associated with this pattern. This enables them to activate scripts (Schank & Abelson, 1977) that enable them to act, perhaps immediately, via symptomatic rules (S-Rules) that guide their behaviors.

	Decision	State-Oriented Response	Structure-Oriented response
Recognition & Classification	Frame Available?	Invoke Frame	Use Analogy and/ or Basic Principles
Planning	Script Available?	Invoke Script	Formulate Plan
Execution & Monitoring	Pattern Familiar?	Apply Appropriate S-Rules	Apply Appropriate T-Rules

Table 9. Problem Solving Decision and Responses

If the observed pattern of state information does not map to a familiar pattern, humans must resort to conscious problem solving and planning (Johannsen & Rouse, 1983), perhaps via analogies or even basic principles. Based on the structure of the problem, which typically involves much more than solely observed state variables, they formulate a plan of action and then execute the plan via topographic rules (T-Rules). As this process proceeds, they may encounter familiar patterns at a deeper level of the problem and revert to relevant S-Rules.
This framework has important implications for multi-level modeling of complex socio-technical systems. Succinctly, it may not make sense to represent human behavior and performance for any particular task in Table 8 using one type of model. Scripted behaviors may be reasonable for familiar and frequent instances of these tasks. However, for unfamiliar and/or infrequent instances of these tasks, a more robust representation is likely to be needed.

More recently, Rouse (2007) presents an expanded and updated set of the foregoing models, all premised on the nature of human abilities and limitations that people bring to their tasks. He elaborates estimation, queuing, control and diagnosis models. He also provides models of human behavior and performance in system design, information seeking, multi-stakeholder decision making, investment decision making, strategic management, and enterprise transformation. The overall exposition addresses human behavior and performance in tasks ranging from operation and maintenance of complex systems to managing enterprises and leading them through fundamental change.

Rasmussen (1986, 1994) discusses a range of models for attention allocation, signal detection, manual control and decision making. With regard to decision making, he addresses human judgment, decision theory, behavioral decision theory, psychological decision theory, social judgment theory, information integration theory, attribution theory, fuzzy set theory, scripts, plans and expert systems, and problem solving models. Rasmussen also presents three important conceptual frameworks: the means-ends abstraction hierarchy, levels of human control, and human error mechanisms. These frameworks have significantly influenced the line of reasoning in this report.

Carley (2002, 2009) addresses computational modeling of socio-technical systems. She represents these systems as "synthetic agents composed of other complex, computational and adaptive agents constrained and enabled by their position in a social and knowledge web of affiliations linking agents, knowledge and tasks." She argues that the capabilities of agents (cognitive, communications, information seeking) define what types of "social" behaviors emerge, and concludes that, "The use of computational models enables generation of meaningful insights and the evaluation of policies and technologies."

Carley and Frantz (2009) discuss a set of computational tools for simulation of social systems. They build on a meta-matrix representation of who is connected to who and the nature of the connections. Their methods and tools include DyNetML, a universal data exchange format for social network data; Automap, a software tool for extracting semantic networks and meta-networks from raw, free-flowing, text-based documents; Organization Risk Analyzer, a software tool that computes social network, dynamic network, and link analysis metrics on single and meta-network data; and CONSTRUCT, a software tool that provides a platform to supports virtual experimentation with meta-matrix data.

Barjis, (2011), Carley (2002b), Cioffi-Revilla (2010) and Dietz, 2006 discuss a variety of methodological considerations related to the characteristics of socio-technical and natural systems and defining features of simulation models. They elaborate the notions of enterprise ontologies, enterprise governance and enterprise architecture. This material represents recommended ways of thinking about modeling complex socio-technical systems more than presenting models per se.

5.0 COMPARISON OF DOMAINS

Table 10 shows how the multi-level modeling framework can be applied in three different domains: healthcare delivery, energy consumption, urban resilience, and military operations. Application of the framework involves representing the phenomena at each level, choosing models to represent these phenomena, selecting computational means to operationalize these models across levels, including the flow of information, e.g., on incentives, within and between levels as indicated in Figures 2 and 3. All of these components provide the "engine" for developing interactive visualizations to enable exploration of alternative system designs at multiple levels, e.g., process designs vs. policy rules.

Considering the healthcare delivery example, models at the work practices level would include models of patient disease incidence and progression, as well as clinical decision making. Delivery operations would be modeled as process flows, including information flows. Models at the system structure level would be drawn from microeconomics to predict organizations' process investment decisions. The domain ecosystem would be modeled using rule-based policies, for example, for alternative payment schemes.

Level	Healthcare Delivery	Energy Consumption	Urban Resilience	Military Operations
Domain Ecosystem	Social Priorities, Medicare/ Medicaid	Public Service Commission	Regional, State, City Governance System	Military Priorities, Rules of Engagement
System Structure	Providers, Payers, Suppliers	Utilities, Builders, Contractors	Mayor, Council, City Planning, Emergency Mgt	Commanders, Service Components
Delivery Operations	Care Capabilities, Health Information	Generation, Trans, & Distribution	Flows Within Delivery Infrastructures	Strategies, Tactics, Battle Plan
Work Practices	Patient-Clinician Interactions	End-User Consumption	People Consuming Food, Water, Energy, Etc.	Movement of Forces, Platforms, Etc.

Table 10. Comparison of Domains

A multi-level model for energy consumption would be populated as follows. At the work practices level, consumers' multi-attribute utility functions would describe their tradeoffs among reduced energy bills, investments and effort involved, and value attached to contributing to environmental sustainability. These models would likely differ among different segments of the population. Social network models, particularly of younger households, could portray how people work together and possibly compete to save the most energy. At the delivery operations level, the generation, transmission and distribution of energy would be modeled, with variations for the roles that renewables such as solar, wind, and waves might play. Systems structure models would include microeconomics model of the key stakeholders and how they address the alternative investments in this arena, including how utilities address dynamic pricing within the rules of the game defined at the domain ecosystem level by the public service commission.

The military operations example is representative of a wide range of multi-level models and simulations developed over many decades (Mullen, 2013). This rich legacy provides ample evidence that multi-level models and simulations are eminently feasible. A central problem has been the time and money required to develop them. It is later argued that the foundation provided by this report can improve this situation.

The resulting interactive, computational model can be termed a "policy flight simulator" (Rouse, 2013). Such simulators can provide the means to explore a wide range of possibilities, thereby enabling the early discarding of bad ideas and refinement of good ones. This enables *"driving the future before writing the check."* One would never develop and deploy an airplane without first simulating its behavior and performance. However, this happens all too often in organizational decision making in terms of policies, strategies, plans, and management practices that are rolled out with little, if any, consideration of higher-order and unintended consequences.

6.0 AN ILLUSTRATIVE EXAMPLE: COUNTERFEIT PARTS

6.1 OVERVIEW

Potential enterprise modeling problems are ubiquitous in government and industry. To illustrate our multi-level modeling methodology, we select a case study involving the enterprise problem of counterfeit parts in the supply chain for Department of Defense (DoD) systems. This problem has gained increasing attention and concern in recent years, particularly the issue of counterfeit hardware or software that may endanger operational performance and safety (GAO, 2010).

Counterfeit parts fall into two major categories – parts designed with malicious intent and those designed with intent to defraud. While having different characteristics, both can have serious consequences. The former may escape detection, due to intent to provide malicious functionality under certain conditions and normal operation otherwise. The latter may fail due to quality issues after an initial period of satisfactory performance. Fraudulent counterfeits include parts re-marked to make them appear as original equipment manufacturer (OEM) or original component manufacturer (OCM) parts, defective parts passed off as functional, or parts scavenged from scrapped assemblies without proper documentation.

Counterfeit parts have been documented in a wide array of defense systems, with the largest source of such parts coming from China (Senate Armed Services Committee, 2012). Such parts can have significant adverse effects on system reliability, resulting in increased downstream costs.

Counterfeit parts have emerged as a serious issue due to a number of trends in defense systems, as well as the global economy.

- Modern systems are increasingly complex in terms of their sheer number of components. When these components need to be replaced or upgraded, the process of ensuring counterfeit avoidance is, clearly, more difficult than would be the case if there were fewer components.
- Systems typically are being used in service for much longer than originally anticipated. Thus, replacement parts and upgrades must be provided for a greater than anticipated time frame. A well-known phenomenon in the defense industry is that of supplier diminishment. Over time, the number of suppliers for a particular component diminishes, as the original equipment manufacturer or original component

manufacturer either exits the market or goes out of business, or as new technologies are developed requiring new replacement parts (AIA, 2011).

- At the same time, globalization has resulted in a dramatically increased percentage of electronic components made overseas. These components pose the most risk to the DoD supply chain, especially as these suppliers are used extensively by commercial supply chains, leaving DoD with little leverage (AIA, 2011). Foreign suppliers tend to involve more risk in terms of providing counterfeit parts than domestic ones.
- Concurrent with the globalization trend are two trends within defense acquisition programs and major system integrator firms. First, major defense programs are seeking to cost-share acquisition costs with other governments through sales of systems to those governments. The inducement used for this is to locate part of the industrial base for a particular program in the other countries whose governments are would-be customers (Kapstein, 2004). Second, prime contractors have evolved into true system integrators that assemble major sub-systems produced by partner firms, as opposed to manufacturers that primarily source smaller sub-assemblies and components for their assembly operations (Tang, 2009). Thus, the prime relinquishes substantial control over its supply chain by decentralizing design and production, making counterfeit mitigation potentially more difficult.
- Use of the internet has increased the anonymity of part sources. This has provided a means by which counterfeit parts can more easily be inserted into the supply chain. For instance, GAO (2012b) conducted a study and found counterfeit parts were available on internet purchasing platforms used by DoD.

A variety of different counter-measures are available to address counterfeit parts. In the acquisition phase of the system lifecycle, these include:

- Program Protection Plans, which articulate measures to protect security of a program,
- Criticality analysis, which indicates what sub-systems and components are mission-critical and thus should have stricter supply chain oversight (e.g., through sourcing from trusted suppliers),
- Software assurance, which seeks to ensure that software functions as intended, free from intentional or unintentional defects,
- Robust system design methods, whereby a system can still function with counterfeit components or potentially experience graceful degradation, and
- Trusted system design methods, whereby a system detects or disallows counterfeits.

In the sustainment phase of the system lifecycle, counterfeit counter-measures include:

- Use of trusted suppliers for replacement parts and upgrades,
- Subsidy of OEMs to continue making replacement parts and upgrades,
- Supply chain monitoring (prevent, detect, respond),
- Incentives to primes and secondaries to monitor their sources,

- Reporting and information-sharing via databases set up for counterfeit incident documentation,
- Traceability of components throughout the supply chain,
- Penalties for counterfeiting, and
- Intelligence gathering and observations on defense supply chains.

Many of these options are included in official DoD policies addressing security and counterfeiting (DoD 2011; DoD, 2012; Kendall, 2012).

Each of these counter-measures has costs associated with it. For instance, robust or trusted system design methods have investment costs for research and development, and then likely operational costs for systems engineering in actual programs. Use of trusted suppliers may limit supply, causing increased part costs or decreased part availability. Supply chain monitoring incurs inspection and other costs. Costs may be borne by different actors in the enterprise, depending on the particular counter-measure. Thus, there may be unanticipated behavioral responses. The fundamental question is which portfolio of counter-measures should receive investments to mitigate the problem of counterfeits?

It should be noted that two programs exist for reporting and documenting product data for government procurement, and are to be used for counterfeiting incidents. GIDEP (Government-Industry Data Exchange Program) is to be used for reporting by industry. PDREP (Product Data Reporting and Evaluation Program) is to be used by government agencies.

Additional information on the issue of counterfeit parts can be found in (ABA, 2012; Dept. of Commerce, 2012; GAO, 2011, 2012a; Livingston, 2007a, 2007b; McFadden & Arnold, 2010; Pecht & Tiku, 2006; Stradley & Karraker, 2006).

6.2 Enterprise Problem Characteristics

Clearly, this is an enterprise problem due to the multi-organizational aspect of system acquisition and sustainment practiced by DoD. Organizations involved include various DoD agencies, services and commands, thousands of suppliers organized in tiers, plus a variety of federal agencies with jurisdiction over various aspects of the problem, and finally Congress. Government agencies and Congress are concerned with developing and implementing laws and policies to reduce or eliminate the risk of counterfeit parts via testing and interdiction or use of trusted/certified suppliers. A variety of considerations must be weighed, some of which affect the entire enterprise, and some of which affect individual actors. Cost and availability of spare parts versus safety and expected performance of systems serve as one set of examples. These issues may have disproportionate effects on certain enterprise actors, depending on policies and practices used to address the problem. Thus, actors are incentivized to behave in certain ways, some intended and some unintended by policy-makers.

As an enterprise problem, there are both technical and socio components. Clearly, the technical aspects of the problem include:

- Systems engineering design in acquisition,
- Sustainment networks and part flows,
- Inventories,
- Inspection regimens, and
- Trusted supplier designation based on objective criteria.

The socio components include the following

- Trust and collaboration,
- Communication,
- Information-sharing, and
- Reaction to incentives.

6.3 Conceptual Model

Decisions, actions and outcomes may occur in different areas of the enterprise, ranging from the enterprise level to the level of a single actor or individual. This section presents a conceptual model of this breakdown for the counterfeit parts case study. Table 11 shows the important constituent elements of each level.

Level	Elements
Ecosystem	U.S. Government, Department of Defense, industrial base, economy, tax base, foreign governments, macro-trends
System structure	Program structure (acquisition and sustainment), integrated product teams, specific customers, supplier network
Delivery operations	Acquisition processes and milestones, sustainment operations, design facilities, factories, bases, repair depots, inspection facilities, delivery channels
Work practices	Systems engineers, program managers, sustainment engineers, logisticians, test and evaluation personnel, counterfeiters

Table 11. Multi-Level Domain Elements

In the succeeding sub-sections, we use systemigrams (Blair et al., 2007) to illustrate the relationships between different components of the overall enterprise model both between levels and within levels. The intent here is to provide an overall context for the enterprise problem that can be used to develop specific models to answer more narrowly focused questions that appeal to the needs of specific clients.

6.3.1 DOMAIN ECOSYSTEM

The domain ecosystem for the counterfeit parts case study consists of the Department of Defense, the U.S. government and relevant security-related agencies, the defense industrial base, the overall economy and tax base that supports defense appropriations, macro-trends that impact current and future defense programs, and policies and laws that govern acquisition, sustainment and counterfeiting. The ecosystem is depicted in Figure 4.

The industrial base provides platforms, major sub-systems, sub-systems and components for defense systems. The industrial base is influenced by macro-trends such as globalization, outsourcing and off-shoring, joint ventures with foreign governments, and new business models for system design and production. Such trends may expose programs in the ecosystem to counterfeiting risks from sources that have either strategic or economic motivations.

As a program transitions from acquisition to sustainment, its industrial base shifts from design and production to sustainment. Sustainment typically operates as a private-public partnership, as government depots play a substantial role. Such concepts as performance-based logistics come into play, as well, whereby a prime contractor is contracted to provide a certain performance level in terms of metrics such as system availability. Macro-trends in sustainment include increased system life spans and technology advancements. The ecosystem sees aggregate outcomes from counterfeiting in terms of the effect on overall mission.

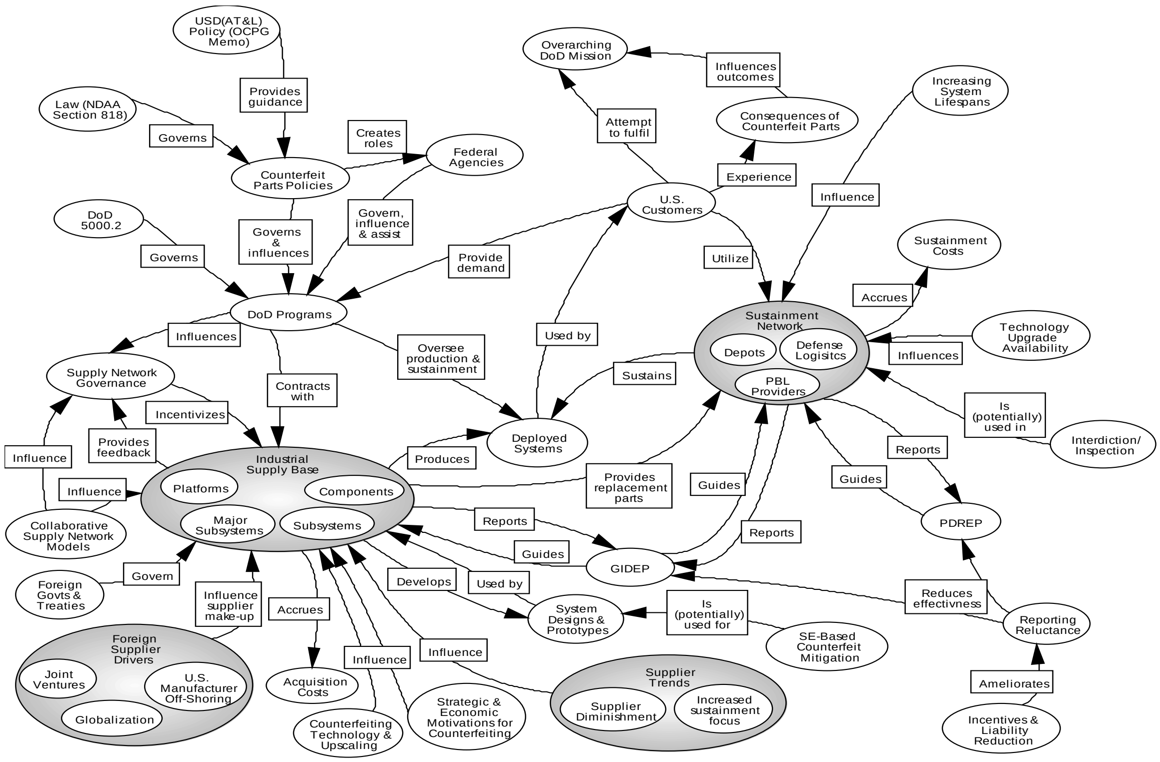


Figure 4. Ecosystem

6.3.2 System Structure

The system structure, shown in Figure 5, level focuses on the various organizations (agencies and firms) that interact with one another in the acquisition and sustainment enterprise. There is typically a networked structure here, with some amount of hierarchy.

Any particular program is overseen by DoD's Acquisition, Technology & Logistics office. The industrial base provides suppliers, plus the prime contractor, for a program. A program's supply chain typically is organized as a set of tiers consisting of hundreds or even thousands of suppliers. A supplier in the second tier, for example, provides parts to suppliers in the first tier. This tiered organization is not necessarily hierarchical, as a particular firm may be in more than one tier. In addition, a firm may be in multiple programs and may collaborate with another firm in one program and compete with the same firm for another program's contract.
As a program moves from acquisition to sustainment, many of its suppliers will continue to supply replacement parts for use at different sustainment facilities. However, other firms from the industrial base will be added to the program as the original suppliers may elect not to continue, or not be able to continue. Contractors are supposed to report counterfeit incidents to GIDEP, which is accessible by other firms for supplier monitoring. Likewise, government agencies are supposed to report such incidents to PDREP.

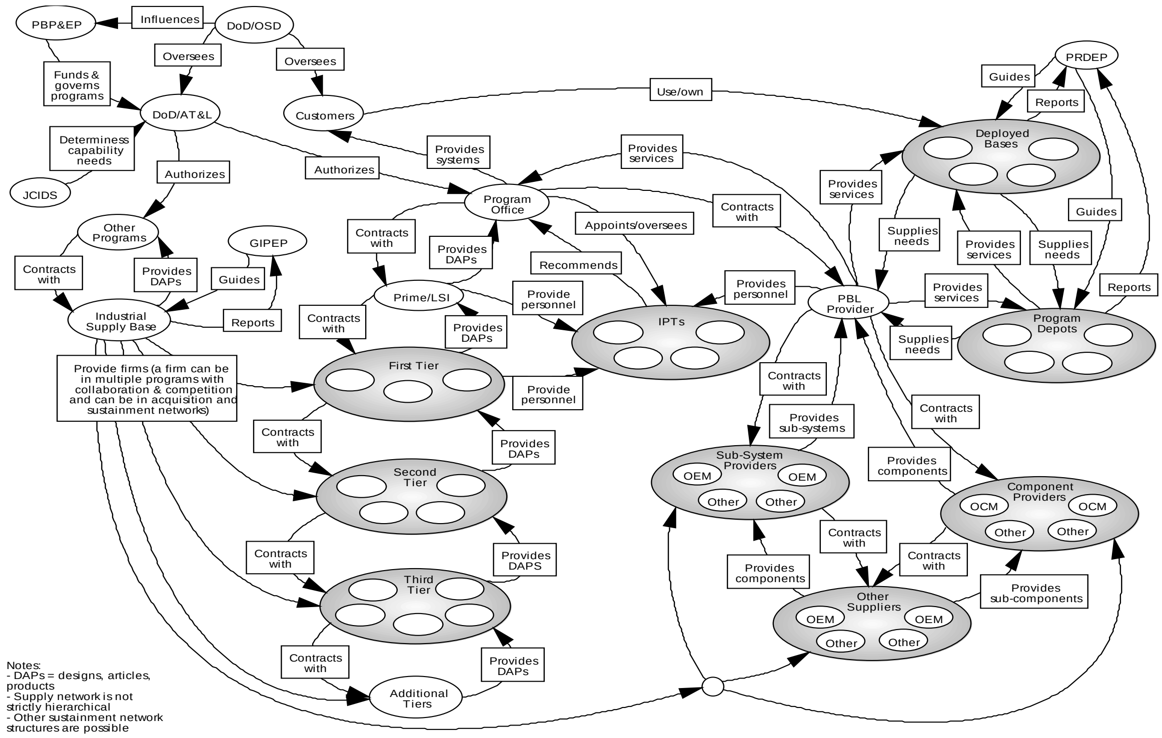


Figure 5. System Structure

6.3.3 Delivery Operations

The delivery operations level focuses on the various processes and facilities at which they are performed (Figure 6). The supply network is cast as a series of facilities that engage in design collaboration between the prime and sub-contractors, part flows that eventually result in major sub-systems being integrated in final assembly and finally cost accruals. These activities take place in the context of acquisition phases as spelled out in DoD 5000.2. Designs and articles pass from one acquisition phase to another as the acquisition matures. The program office oversees this set of processes and communicates and enforces various regulations, including counterfeiting counter-measures.

Systems are delivered to deployed bases from the production processes and facilities. Field maintenance and repair is done at these facilities, while systems are sent to depots or contractor maintenance and repair facilities for depot-level work. Parts for maintenance and repair are held in inventories. Inspection procedures may be used there.

While the figure does not show it explicitly, it should be understood that the supply network facilities evolve over time, with new ones being added and current ones falling out of the network, as a program moves from acquisition and production to sustainment. It is here that the phenomenon of diminishing supply takes hold.

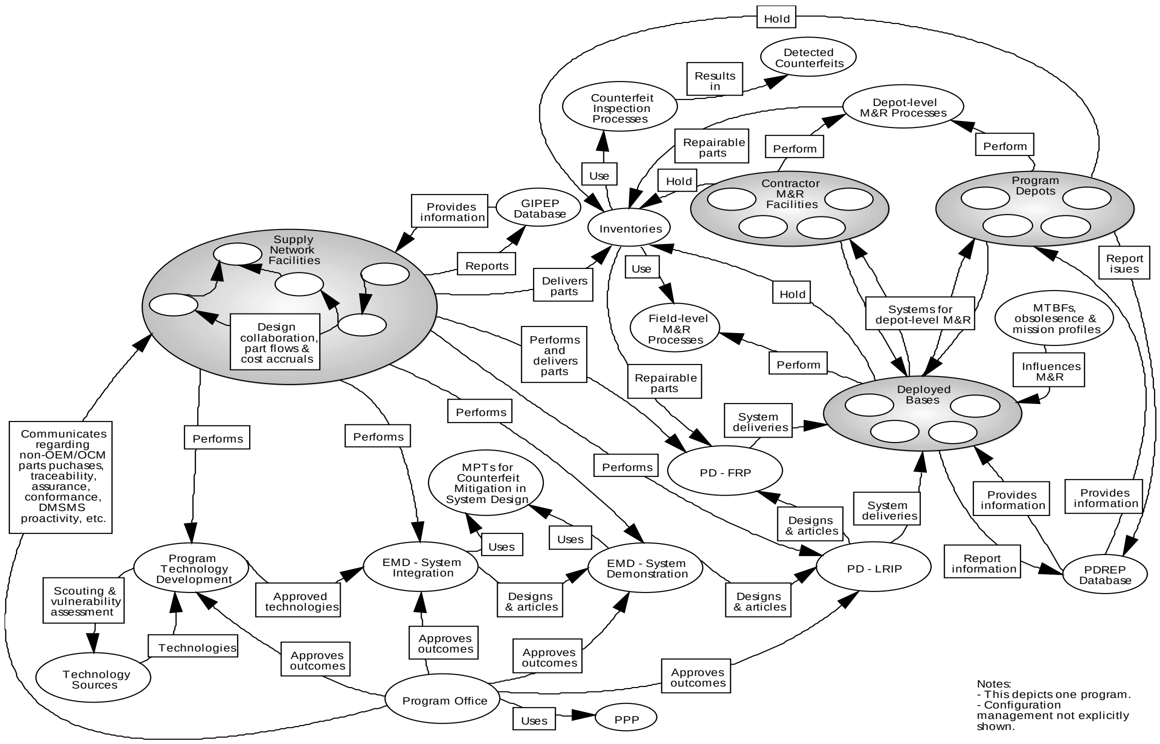


Figure 6. Delivery Operations

6.3.4 Work Practices

The work practices model consists of the individual people in the acquisition and sustainment enterprise, as well as the work that they perform and how they interact with one another. The emphasis is on acquisition and sustainment professionals in a program setting, as shown in Figure 7. A program manager oversees the program and has a variety of government professionals reporting to him or her in functional roles.

For instance, a chief systems engineer would report to the program manager. The chief systems engineer may have other engineers reporting to him or her. The government systems engineers would then provide oversight for the systems engineers of the prime contractor to ensure that the government's interests are represented. Typically, the systems engineers of the contractor(s) provide most of the work for system design and development. However, different philosophies of division of labor between government and contractor may come into play over time. Thus, the model should provide flexibility in this regard. The systems engineers of the prime contractor then provide oversight for the systems engineers of each sub-contractor. Usually, the government systems engineers do not have direct oversight or contact with those of the sub-contractor unless it is through the prime.

Similarly, there is government oversight of the prime workforce in the other functional areas, with the prime then providing oversight of the functional areas of the various sub-contractors. The workforce performs tasks as governed by DoD 5000.2 related to design, development, testing, maintenance, repair, etc. To address specific issues that overlap functions, workforce members participate in integrated product teams (IPTs). There are likely specific counterfeiting counter-measures done at the individual level (e.g., adherence to guidelines or testing regimens) called out explicitly.

The overall workforce is affected by several phenomena such as training (skills and skill levels), social networks (cooperation among individuals), collaboration (cooperation between functions) and trust. Social networks can be shown in much more detail as relationships between individuals within a program, whereas trust tends to be more of a field effect.

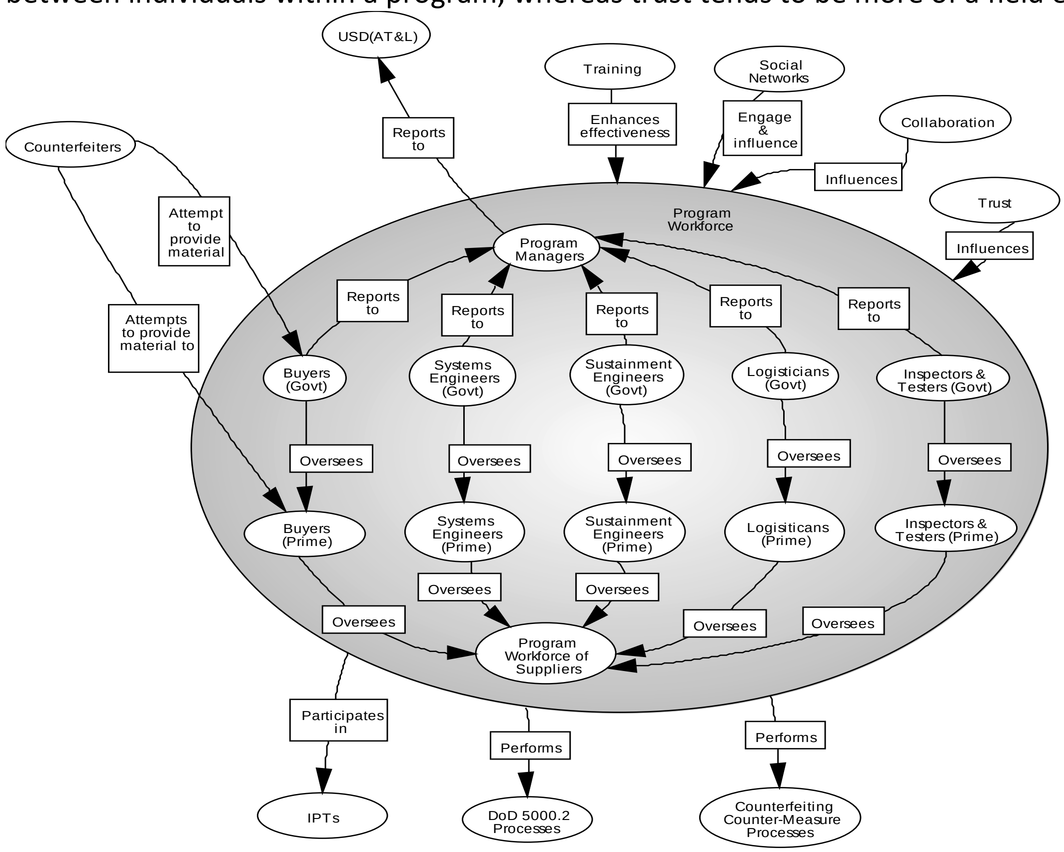


Figure 7. Work Practices

6.3.5 Relationships between Levels

Each level has relationships with the other levels, as shown in Figure 8. For instance, the ecosystem provides the incentive structure (e.g., contract types, penalties for counterfeiting, available funding) and policies downward, while it receives performance information (cost, mission effects) from below. Figure 8 also shows the typical relationships between elements within each level on the left side of the figure.

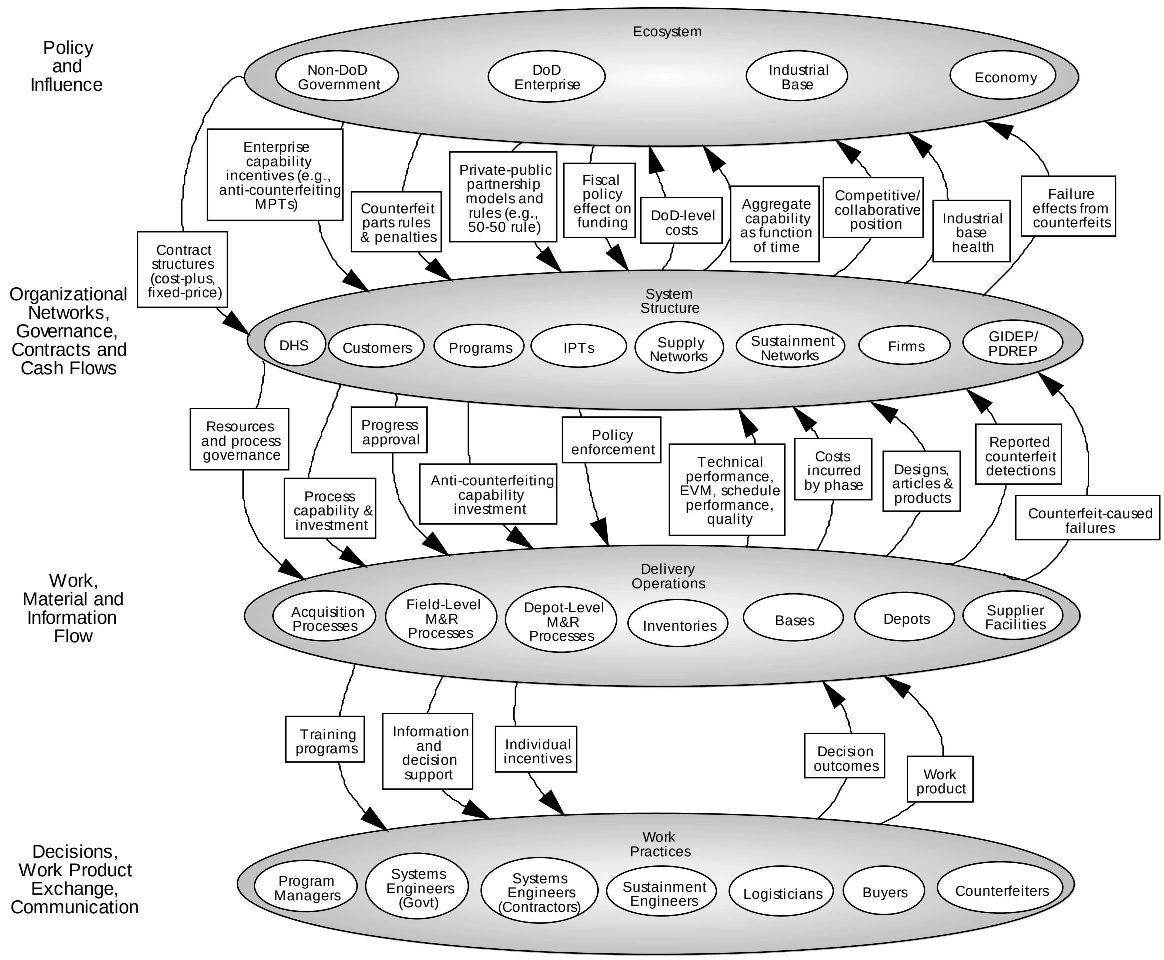


Figure 8. Relationships between Levels

Each level has performance metrics associated with it, as well. The ecosystem, for instance, focuses on mission-level and industrial base performance. The work practices level, on the other hand, focuses on individual performance in terms of decision quality and work product, as well as collaboration performance (e.g., between functions such as systems engineering and logistics). The performance metrics are shown in Table 12.

Level	Performance Metrics
Ecosystem	Mission-level performance - Effect of counterfeiting on mission achievement Industrial base-level performance - Percentage of disqualified firms per segment - Percentage of OEM and trusted supplier firms used per segment - Number of single-source firms (OEM, trusted, other) Program portfolio-level performance - DoD-wide cost of counterfeit interdiction/remediation
System structure	Firm-level performance - Extra costs associated with counterfeit prevention/remediation - Lost contracts due to counterfeiting problems Program-level performance - Extra cost of counterfeit prevention/remediation - Extra cost due to counterfeit discoveries (e.g., extra repair) - Fleet availability cost due to failures
Delivery operations	Operation-level performance - Number of counterfeits detected via failures - Number of counterfeits detected via inspection - Inspection cost per facility/process - Failure cost (downtime, repair, etc.)
Work practices	Individual-level performance - Decision quality - Work product quality - Counterfeits discovered/undiscovered Collaboration performance - Joint functional collaboration

Table 12. Performance Metrics

6.4 Analysis Scenarios

This section discusses four scenarios around which specific models can be developed for analysis. These scenarios are presented in Table 13, which provides a short description, motivating questions and types of models needed.

The intent is to be able to derive these models in a principled manner from the case study context presented in previous sub-sections. This is a substantial research challenge and involves, at least in one approach, specifying a computational framework that embodies the contextual model. This framework could then serve as a library for enterprise models, at least in domains related to counterfeit parts in the DoD supply chain. Such a framework and library should have a methodology for managing assumptions made in specific models relative to other models and to the library components and framework.

Scenario	Questions	Models
A major foreign supplier is influenced by its government to introduce malicious counterfeits into multiple programs	• What counter-measures are most effective enterprise-wide (across multiple measures)? • Was strength of program adoption of counter-measures a factor in program avoidance of adverse effects?	• Ecosystem – Combinations of counter-measures as policies • System structure – multiple program networks with program offices and tiered suppliers, micro-economic models of firm behavior, game theory interactions between actors • Delivery operations – discrete-event simulations of program progress, part deliveries and logistics, etc., incorporating effectiveness of following policies • Work practices – agent-based models of individuals and skills and skill levels
A second-tier supplier has one of its test processes compromised, since it has determined it cannot produce parts cost-effectively within its fixed price contract	• Can this be detected given the output stream of parts and the downstream inspection processes? • What incentives should be applied to the prime to avoid this situation?	• Ecosystem – Incentive alternatives for suppliers • System structure – game theory interaction models between supplier and its customer and program • Delivery operations – discrete-event simulations of part outputs and inspection processes • Work practices – agent-based models of individuals and skills and skill levels
DoD is faced with investment decisions involving research into trusted systems and robust systems	• Where should these investments be made and how long will they take to yield results? • How effective will they be, given that the counterfeiters may develop new methods?	• Ecosystem – Available funding and priorities, threats • System structure – R&D agencies and contractors, research strategies at firm level • Delivery operations – discrete-event models of investments into staged research programs and outputs with probabilistic success outcomes due to technical failures and changing threat profiles • Work practices – agent-based models of individuals and skills and skill levels
DoD is initiating a new program. The traditional way of business is that the prime conducts in-house design & manufacturing and out-sources components. Recent years have seen outsourcing of major assemblies, some to foreign suppliers. Problems have ensued with this business model.	• Which business model should be adopted, especially with respect to counterfeit parts vulnerability? • What counter-measures should be enacted to support either model?	• Ecosystem – Macro-economic models, system dynamics models for economic cycles, available counter-measure policies • System structure – collaborative network of partnered firms for program vs. command-and-control structure for program • Delivery operations – discrete-event simulations of program progress, production and logistics reflecting different program models • Work practices – agent-based models of individuals and skills and skill levels

Table 13. Scenarios

The intent is to be able to derive these models in a principled manner from the case study context presented in previous sub-sections. This is a substantial research challenge and involves, at least in one approach, specifying a computational framework that embodies the contextual model. This framework could then serve as a library for enterprise models, at least in domains related to counterfeit parts in the DoD supply chain. Such a framework and library should have a methodology for managing assumptions made in specific models relative to other models and to the library components and framework.

The next section expands on this notion of a computational framework and related topics with directions for future research in enterprise and socio-technical modeling.

7.0 Research Issues

This report presents a conceptual framework for multi-level modeling of complex socio-technical systems, provides linkages to the historical roots and technical underpinnings of this framework, and outlines a catalog of component models for populating multi-level models. Thus, the framework rests on an impressive body of knowledge.

However, there are several fundamental issues that need to be addressed for this endeavor to mature and be widely employed by systems scientists and engineers. The issues and questions outlined in this section need to be resolved if multi-level modeling is to move beyond the current state of each instantiation of this approach being an idiosyncratic and often heuristic creation by modelers who are unaware of the foundation upon which they can build.

7.1 Decomposition

The starting point for multi-level modeling is the decomposition of an overall phenomenon, e.g., healthcare delivery, into component phenomena at varying levels of abstraction and aggregation. A central question at this point is what phenomena belong in each of the multiple levels? Further, how does the representation of each phenomenon depend on its level? This can be addressed in part by considering natural part-whole relationships. However, the question remains what wholes and what parts are needed to address the question that motivated the modeling initiative?

As an aside, it is important to emphasize the need to be very clear at the outset about what questions the model is intended to address. When the only objective is to develop a model, and the questions to addressed remain elusive and ambiguous, the natural tendency of modelers is to include everything they can imagine that will ever be needed. The result tends to be an unwieldy composition that is difficult to understand and maintain.

7.2 Mapping

The choice of which phenomena will be represented at each level leads to choices of how to characterize each phenomenon. The catalogs of models discussed earlier can be quite helpful in this regard. Each representation will have defined input-output variables. The next question is what variables cross the levels between representations? Further, what transformations are needed to connect across levels? Basic issues here include units of measure, coordinate systems, and time. Zeigler (2000) addresses these issues within the context of dynamic systems.

It is important to note that resolution of these basic issues is necessary but not sufficient for assuring Tolk's (2003) semantic interoperability. Being able to connect two models and have them jointly compute some outputs does not assure that these outputs are valid and meaningful. The issue here is one of "assumption management." Are the assumptions of the two or more interconnected models compatible? This is straightforward when the modelers are the creators of all the component models, but far from easy when some of the component models are legacy software codes.

7.3 Scaling

It is often the case that models begin with only a small number of simulated agents (e.g., patients) or only a fraction of the entire transportation network that is of interest. The intention is to scale up such smaller models to address the whole problem of interest once experience and confidence is gained with the initial models. Scaling is often very difficult and results in large unfathomable models that compute very slowly. The modelers can lose any intuitions of what is happening in the scaling process.

The first question is, given the targeted scale of the modeling effort, what should be the unit of scale for each phenomenon? A related question is by what quantum does each unit scale? Perhaps millions of patients are better simulated as cohorts rather than individuals. Perhaps the flow of thousands of vehicles should not start with the dynamics of each vehicle, but instead consider waves of vehicles.

7.4 Approximation

The creation of large multi-level models inevitably requires using approximations. The central question is what means are best used for data and computational efficiencies? For example, what probability distributions are used for arrival and service times in a discrete event simulation? Triangular distributions might be much easier to implement than lognormal distributions, compute much faster once implemented and, very importantly, have parameters that are much easier to estimate.

One needs to ask about the implications of different choices? For example, defining agents as cohorts of patients rather than individual patients will reduce the variability across patients. If this variability is the primary issue of importance, some countermeasure for the variance reduction may be needed. In general, small scale examples can often be used to gain understanding of how the effects of approximations propagate.

7.5 IDENTIFICATION

The question of interest here is how can structural properties of processes be inferred from design and operational data sets? This is important because many complex systems have no "as is" blueprints, i.e., such systems emerged rather than being designed. Instead, one may have data on millions of transactions throughout the system's processes. One needs to have algorithms that can infer processes from such data sets, often without any baseline process maps to help with validation.

This raises the question of what are the best metrics for characterizing the "fit" of an inferred process to a data set? For identifying input-output relationships, one could use mean-squared-error as the metric. However, for process maps where relationships among nodes are the concern, one is fitting networks to data rather than equations. In this case, one might use something like percentage of empirical relationships captured by the network representation.

7.6 PARAMETERIZATION

Structural representations of processes will usually have parameters such as rates, means, and probabilities that need to be estimated. In order to estimate these parameters, one first has to address the question of how data sets can be accessed and normalized across elements of the enterprise. For example, within healthcare, how can clinical, financial and claims data sets be combined, while maintaining patients' identities and rationalizing varying time scales?

Once data sets are combined and rationalized, how can unbiased parameter estimates best be obtained from the integrated data set? A key issue is assuring that the data set used for estimating parameters is representative of the population for which predictions are sought. A more refined concern is estimating parameters for baseline "as is" systems versus potential "to be" systems.

7.7 PROPAGATION

Structural and parametric uncertainties can have far-reaching effects as they propagate across representations and levels of the overall model. This raises the question of how uncertainties can best be propagated across multiple representations at multiple levels? In particular, how is the variability associated with one level propagated to other levels when simple propagation of point estimates is unwarranted?

Various mechanisms might be adopted, but how are levels of variability attenuated or accentuated by different approaches to propagation? The key issue is that approximations can have effects beyond the immediate impacts motivating the approximations. This can be a rather complicated issue and have significant higher-order effects and unintended consequences.

7.8 VISUALIZATION

If multi-level models are to be used to support a wide range of decision makers, the model outputs have to be accessible by people who are far from modeling and simulation experts. This raises the question of how the "state" of a multi-level system can best be characterized and portrayed. The answer to this question should be determined by the nature of visualizations most meaningful to the key stakeholders in regard to the questions targeted via the multi-level model.

Beyond portraying the state of the system, stakeholders are often concerned with the nature of relationships between levels of the model. How can the relationships within a multi-level system best be portrayed to enable experimentation and insights? This question concerns how best to enable stakeholders to manipulate the relationships between levels of the overall model. Once stakeholders are "in the loop" of choosing assumptions and manipulating parameters, stakeholder buy-in is usually greatly enhanced.

7.9 CURATION

Section 4.0 outlined a wealth of component models for potential inclusion in multi-level models. However, this wealth is not often used. This is due to both a lack of knowledge of these resources and difficulty in accessing them (Rouse & Boff, 1998). Professionals in modeling and simulation seldom access the academic journals originally reporting these models. Even when practitioners are aware of such publications, they are seeking computer codes, not research treatises.

How can component models be represented, archived, maintained, and accessed to facilitate rapid model integration? Put simply, these resources need to be curated. There needs to be one point of access for the many hundreds of models discussed in Section 4.0. This access should enable downloading computer codes, documentation on assumptions and use, and original reports of the development and validation of these models. Of course, this begs the basic question of how participating organizations can be incentivized to contribute to and make use of the curated archive?

8.0 CONCLUSIONS

Complex engineered and natural systems can be characterized as complex adaptive systems where independent, yet interactive, intelligent agents pursue their goals, often in conflict with other agents, and learn and adapt to the changing ecosystem. A multi-level approach to computationally modeling the functioning of such socio-technical systems can provide the means to understanding and then transforming such systems.

This report has presented a conceptual framework for multi-level modeling of complex socio-technical systems, provided linkages to the historical roots and technical underpinnings of this framework. It has also outlined a catalog of component models for populating multi-level models. A proposed framework was given for multi-level modeling of socio-technical systems, including discussion of the phenomena typically associated with each level, as well as wide range of models of human behavior and performance. A comparison of multi-level representations within different domains and an illustrative in-depth example were presented. Finally, fundamental research issues underlying multi-level modeling of complex systems were summarized.

There are significant benefits of adopting the approach advocated in this report. First and foremost, the results will be better models and simulations of complex socio-technical systems. Behavioral and social phenomena are often central to the questions motivating development of models, yet these phenomena are often approached in very rudimentary ways. Much richer representations are certainly possible.

Multi-level modeling with associated interactive visualizations make models and simulations much more accessible to a wider audience of key stakeholders, such as senior decision makers. The abilities to interactively explore alternative strategies, policies and plans enable broader and faster consideration of alternatives. The result tends to be greater “buy in” to emerging and eventual decisions (Rouse, 2013).

Finally, as progress is made on the issues discussed in Section 7.0, these benefits of multi-level modeling with be realized faster and more cheaply. Multi-level models and simulations are much more likely to be employed when it does not take many months or even years, and hundreds of thousands or even millions of dollars, to obtain these capabilities. This report provides the foundation for gaining the benefits outlined in this section.

9.0 REFERENCES

ABA (2012). A white paper regarding Department of Defense implementation of Section 818 of the National Defense Authorization Act for Fiscal Year 2012. Report issued by Task Force on Counterfeit Parts of the Committee on Acquisition Reform and Emerging Issues of the American Bar Association Section of Public Contract Law, October 5, 2012.

Ackoff, R. & Emery, F. (1972). On Purposeful Systems: An Interdisciplinary Analysis of Individual and Social Behavior as a System of Purposeful Events. Chicago: Aldine-Atherton.

Ackoff, R.L. (1971). Toward a System of Systems Concepts. Management Science. 17 (11), 661-671.

Ackoff, R.L. (1974). Redesigning the Future: A Systems Approach to Societal Problems. New York: John Wiley & Sons.

Ackoff, R.L., Churchman, C.W., & Arnoff, E.L. (1957). Introduction to Operations Research. New York: John Wiley & Sons.

Adams, K.M., Hester, P.T., Bradley, J.M., Meyers, T.J., & Keating, C.B. (2013). Systems theory as the foundation for understanding systems. Systems Engineering, in press.

AIA (2011). Counterfeit parts: Increasing awareness and developing countermeasures. Arlington, VA: Author.

Arrow, K. J., (1951). Social Choice and Individual Values. New York: Wiley.

Arrow, K. J., & Debreu, G. (1954). Existence of a competitive equilibrium for a competitive economy. Econometrica, 22 (3), 265–90.

Ashby, W.R. (1952). Design for a Brain. London: Chapman & Hall.

Ashby, W. R. (1956). An Introduction to Cybernetics. London: Chapman & Hall.

Baldwin, W.C., Sauser, B., Boardman, J., & John, L. (2010). A Typology of Systems Paradoxes. Information Knowledge Systems Management, 9 (1), 1-15.

Barjis, J. (2011). Enterprise modeling and simulation within enterprise engineering. Journal of Enterprise Transformation, 1, 185-207.

Basole, R.C., & Rouse, W.B. (2008). Complexity of service value networks: Conceptualization and empirical investigation. IBM Systems Journal, 47, (1), 53-70.

Basole, R.C., Rouse, W.B., McGinnis, L.F., Bodner, D.A., & Kessler, W.C. (2011). Models of complex enterprise networks. Journal of Enterprise Transformation, 1 (3), 208-230.

Batarseh, O., & McGinnis, L. F. (2012). System modeling in SysML and System Analysis in ARENA. In C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A.M. Uhrmacher (Eds.), Proceedings of the 2012 Winter Simulation Conference.

Beer, S. (1984). The Viable Systems Model: Its Provenance, Development, Methodology and Pathology. Journal of the Operational Research Society, 35 (1), 7-25.

Bellman, R.E. (1957). Dynamic Programming. Princeton, NJ: Princeton University Press.

Bertalanffy, K.L.V. (1951). General system theory - A new approach to unity of science, Human Biology, 23, 303-361.

Bertalanffy, K.L.V. (1968, 1976). General System theory: Foundations, Development, Applications. New York: George Braziller.

Bertalanffy, L.V. (1972). The History and Status of General Systems Theory. Academy of Management Journal, 407-426.

Blair, C.D., Boardman, J.T., & Sauser, B.J. (2007). Communications Strategic Intent With Systemigrams: Application to the Network-Enabled Challenge. Systems Engineering, 10 (4), 309-322.

Booch, G. (1991). Object-Oriented Design with Applications. Redwood City, CA: Benjamin Cummings.

Burton, R.M. (2003). Computational laboratories for organization science: Questions, validity and docking. Computational and Mathematical Organization Theory, 9, 91-108.

Burton, R.M., & Obel, B. (2011). Computational modeling for what-is. What-might-be and what-should-be studies – and triangulation. Organization Science, 22 (5), 1195-1202.

Carley, K. (2002a). Computational organization science: A new frontier. Proceedings of the National Academy of Science, 99 (3), 7257-7262.

Carley, K. M. (2002b). Computational organizational science and organizational engineering. Simulation Modeling Practice and Theory, 10, 253-269.

Carley, K.M., & Frantz, T.L. (2009). Modeling organizational and individual decision making. Handbook of Systems Engineering and Management (Chap. 18). Hoboken, NJ: John Wiley.

Chaitin, G.J. (1974). Information-theoretic limitations of formal systems. Journal of ACM, 21 (3), 409-424.

Checkland, P. (1993). Systems Thinking, Systems Practices. Chichester, UK: John Wiley.

Churchman, C.W. (1971). The Design of Inquiring Systems, Basic Concepts of Systems and Organizations. New York: Basic Books.

Cioffi-Revilla, C. (2010). A Methodology for Complex Social Simulations. Journal of Artificial Societies and Social Simulation, 13 (1), 7-25.

Conant, R. C. (Ed.). (1981). Mechanisms of Intelligence: Ross Ashby's Writings on Cybernetics, London: Intersystems Publishers.

Conant, R.C., & Ashby, W.R. (1970). Every good regulator of a system must be a model of that system. International Journal of Systems Science, 1 (2), 89-97.

Czarnecki, K., & Helsen, S. (2006). Feature-based survey of model transformation approaches. IBM Systems Journal, 45 (3), 621-645.

Dept. of Commerce (2012). Defense industrial base assessment: Counterfeit electronics. Report. Washington, DC: Author.

Dietz, J. (2006). Enterprise Ontology – Theory and Methodology. Berlin: Springer-Verlag.

DoD (2011). DoD supply chain materiel management policy. DoD Instruction 4140.01. Washington, DC: Author.

DoD (2012). Protection of Mission Critical Functions to Achieve Trusted Systems and Networks (TSN). DoD Instruction 5200.44. Washington, DC: Author.

Emery, F. & Trist, E. (1965). The causal texture of organizational environments. Human Relations, 18, 21-32.

Emery, F. & Trist, E. (1973). Toward a Social Ecology. London: Plenum Press,

Flood, R.L., & Jackson, M.C. (1991). Creative Problem Solving: Total Systems Intervention. Chichester. UK: John Wiley.

Forrester, J. W. (1961). Industrial Dynamics. Westwood, MA: Pegasus Communications.

Friedenthal, S. Moore A., & Steiner, R. (2008). OMG Systems Modeling Language Tutorial. Proceedings of International INCOSE Conference, June 15-19.

GAO (2010). DOD should leverage ongoing initiatives in developing its program to mitigate risk of counterfeit parts. Report GAO-10-389, Washington, DC: Author.

GAO (2011). Periodic assessment needed to correct parts quality problems in major programs. GAO-11-404. Washington, DC: Author.

GAO (2012a). Additional efforts needed by national security-related agencies to address risks. Report GAO-12-579T. Washington, DC: Author.

GAO (2012b). Suspect counterfeit electronic parts can be found on internet purchasing platforms. GAO-12-375. Washington, DC: Author.

Gharajedaghi, J. (2011). Systems Thinking: Managing Chaos and Complexity: A Platform for Designing Business Architecture (3rd Edition). Burlington, MA: Morgan Kaufman.

Holland, J. H., & Miller, J. H. (1991). Artificial adaptive agents in economic theory. American Economic Review, 81 (2): 365–71.

Howard, R.A., & Matheson, J.E. (2005). Influence diagrams. Decision Analysis, 2 (3), 127-143.

Jackson, M.C. (2000). Systems Approaches to Management. New York: Kluwer/Plenum.

Jackson, M.C. (2003). Systems Thinking: Creative Holism for Managers. Chichester, UK: John Wiley.

Jackson, M.C., & Keys, P. (1984). Towards a System of Systems Methodologies. Journal of the Operational Research Society, 35 (6), 473-486.

Jacobson, I., Booch, G., & Rumbaugh, J. (1999). The Unified Software Development Process. Reading, MA: Addison-Wesley.

Johannsen, G., & Rouse, W.B. (1983). Studies of planning behavior of aircraft pilots in normal, abnormal, and emergency situations. IEEE Transactions on Systems, Man and Cybernetics, SMC-13 (3), 267-278.

Kahneman, D. (2011). Thinking, Fast and Slow. New York: Farrar, Straus and Giroux.

Kalman, R.E. (1960). A New Approach to Linear Filtering and Prediction Problems. Transactions of the ASME, Journal of Basic Engineering, 82, 34–45.

Kapstein, E. (2004). Capturing Fortress Europe: International collaboration and the Joint Strike Fighter. Survival, 46 (3), 137-160.

Kendall, F. (2012). Overarching DoD counterfeit prevention guidance. Memorandum from Under Secretary of Defense dated March 16, 2012. Washington, DC: Department of Defense.

Kim, C-H, Weston, R.H., Hodgson, A., & Lee, K-H. (2003). The complementary use of IDEF and UML modeling approaches. Computers in Industry, 50, 35-56.

Kiviat, P. J. (1967). Digital Computer Simulation: Modeling Concepts. RAND Memo RM-5378-PR. Santa Monica, CA: RAND Corporation.

Little, J. (2009). Innovation and System Perspectives via Model-Based Design. Proceedings of Dean's Institute, Boston, MA, March 22-25.

Livingston, H. (2007a). Avoiding counterfeit electronic components. IEEE Transactions on Components and Packaging Technologies, 30 (1), 187-189.

Livingston, H. (2007b). Avoiding counterfeit electronic components – Part 2: Observations from recent counterfeit detection experiences. Report. BAE Systems.

Mayer, R.J., Crump, J.W., Fernandes, R., Keen, A, & Painter, M.K. (1995). Information Integration for Concurrent Engineering (IICE) Compendium of Methods Report. Dayton, OH: Wright Paterson Air Force Base.

McFadden, F. E., & Arnold, R. D. (2010). Supply chain risk mitigation for IT electronics. Proceedings of the 2010 IEEE International Conference on Technologies for Homeland Security, 49-55.

McGinnis, L. F., & Thiers, G. (2012). Reference models and data repositories. In W. Kessler, L. McGinnis & N Bennett (Eds.), Enterprise Transformation: Manufacturing in a Global Enterprise (pp. 39-58). Amsterdam: IOS Press.

Mesarovic, M.D., Macko, D., & Takahara, Y. (1970). Theory of Hierarchical, Multilevel, Systems. New York: Academic Press.

Miller, G.A. (1956). The Magic Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information. Psychological Review, 63 (2), 81–97.

Mingers, J., & Rosenhead, J. (2003). Problem structuring methods in action. European Journal of Operational Research, 152 (3), 530-554.

Minsky, M. (195). A framework for representing knowledge. In P.H. Winston, Ed., The Psychology of Computer Vision. New York: McGraw-Hill.

Morse, P.M. (1958). Queues, Inventories, and Maintenance. New York: John Wiley & Sons.

Morse, P.M. (1968). Library Effectiveness. Cambridge, MA: MIT Press.

Morse, P.M., & Kimball, G.E. (1951). Methods of Operations Research. New York: John Wiley & Sons.

Mullen, F.E. (2013). Dynamic Multilevel Modeling Framework Phase 1 -- Feasibility. Washington, DC: Department of Defense, Modeling and Simulation Coordination, Office.

Newell, A., & Simon, H.A. (1972). Human Problem Solving. Englewood Cliffs, NJ: Prentice-Hall.

Parsons, T. (1937). The Structure of Social Action. New York: McGraw-Hill

Parsons, T. (1951). The Social System. Glencoe, IL: The Free Press.

Parsons, T. (1951). Toward a General Theory of Action. Cambridge, MA: Harvard University Press.

Parsons, T., & Smelser, N.J. 1956, Economy and Society: A Study in the Integration of Economic and Social Theory. London: Routledge & Kegan Paul.

Pecht, M., & Tiku, S. (2006). Bogus: Electronic manufacturing and consumers confront a rising tide of counterfeit electronics. IEEE Spectrum, 43 (5), 37–46.

Pew, R.W., & Mavor, A.S. (Eds.). (1998). Modeling Human and Organizational Behavior: Applications to Military Simulations. Washington, DC: National Academy Press.

Pidd, M. (Ed.). (2004). Systems Modeling: Theory and Practice. Chichester, UK: John Wiley.

Pontryagin, L. S., Boltyanskii, V. G., Gamkrelidze, R. V., and Mishchenko, E. F. (1962). A Mathematical Theory of Optimal Processes. New York: Gordon & Breach.

Prietula, M., Carley, K., & Gasser, L. (Eds.). (1998). Simulating Organizations: Computational Models of Institutions and Groups. Menlo Park, CA: AAAI Press.

Proctor, R., Nof, S. & Yih, Y. (Eds.).(2012). Cultural Factors in System Design: Decision Making and Action London: Taylor & Francis.

Rasmussen, J. (1983). Skills, rules and knowledge; signals, signs and symbols, and other distinctions in human performance models. IEEE Transactions on Systems, Man & Cybernetics, SMC-13 (3), 257-266.

Rasmussen, J. (1986). Information Processing and Human-Machine Interaction. New York: North-Holland.

Rasmussen, J., Pejtersen, A.M., & Goodstein, L.P. (1994). Cognitive Systems Engineering. New York: Wiley.

Rasmussen, J., & Rouse, W.B. (Eds.). (1981). Human detection and diagnosis of system failures. New York: Plenum Press.

Rittel, H.W.J., & Webber, M.M. (1973). Dilemmas in a general theory of planning. Policy Science, 4, 155-169.

Robinson, S., Brooks, R., Kotiadis, K., & van der Zee, D-J. (Eds.).(2011). Conceptual Modeling for Discrete-Event Simulation. Boca Raton, FL: CRC Press.

Rouse, W.B. (1980). Systems Engineering Models of Human-Machine Interaction. New York: North Holland.

Rouse, W.B. (1983). Models of human problem solving: Detection, diagnosis, and compensation for system failures. Automatica, 19(6), 613-625.

Rouse, W.B. (2000). Managing complexity: Disease control as a complex adaptive system. Information • Knowledge • Systems *Management*, 2 (2), 143-165.

Rouse, W.B. (2003). Engineering complex systems: Implications for research in systems engineering. IEEE Transactions on Systems, Man, and Cybernetics – Part C, 33 (2), 154-156.

Rouse, W.B. (2005). Thoughts on Complex Systems: An Initial Framework and Discussion Questions. Atlanta, GA: Tennenbaum Institute, October.

Rouse, W.B. (2007). Complex engineered, organizational & natural systems: Issues underlying the complexity of systems and fundamental research needed to address these issues. Systems Engineering, 10 (3), 260-271.

Rouse, W.B. (2007). People and Organizations: Explorations of Human-Centered Design. New York: Wiley.

Rouse, W.B. (2008). Healthcare as a complex adaptive system: Implications for design and management. The Bridge, 38 (1), 17-25.

Rouse, W.B. (2013). Human interaction with policy flight simulators. Journal of Applied Ergonomics, in press.

Rouse, W.B., & Boff, K.R. (1998). Packaging human factors for designers. Ergonomics in Design, 6 (1), 11-17.

Rouse, W.B., & Boff, K.R. (Eds.).(2005). Organizational Simulation: From Modeling and Simulation to Games and Entertainment. New York: Wiley.

Rouse, W.B., & Hammer, J.M. (1991). Assessing the impact of modeling limits on intelligent systems. IEEE Transactions on Systems, Man, and Cybernetics, SMC-21(6), 1549-1559.

Rouse, W.B., Hammer, J.M., & Lewis, C.M. (1989). On capturing humans' skills and knowledge: Algorithmic approaches to model identification. IEEE Transactions on Systems, Man, and Cybernetics, SMC-19(3), 558-573.

Rouse, W.B., & Morris, N.M. (1986). On looking into the black box: Prospects and limits in the search for mental models. Psychological Bulletin, 100(3), 349-363.

Rouse, W.B., & Serban, N. (2011). Understanding change in complex socio-technical systems: An exploration of causality, complexity and modeling. Information • Knowledge • Systems *Management*, 10, 25-49.

Rumbaugh, J., Blaha, M., Premerlani, W., Eddy, F., & Lorensen, W. (1990). Object-Oriented Modeling and Design. Englewood Cliffs, NJ: Prentice Hall.

Schank, R.C., & Abelson, R.P. (1977). Scripts, Plans, Goals and Understanding. Hillsdale, NJ: Lawrence Erlbaum.

Senate Armed Services Committee (2012). Inquiry into counterfeit electronic parts in the Department of Defense supply chain. Report issued May 21, 2012. Washington, DC: Author.

Shannon, C. (1948). A Mathematical Theory of Communication. The Bell System Technical Journal, 27, 379-443, 623-656.

Sheridan, T.B. (1992). Telerobotics, Automation and Human Supervisory Control. Cambridge, MA: MIT Press.

Sheridan, T.B., & Ferrell, W.R. (1974). Man-Machine Systems: Information, Control, and Decision Models of Human Performance. Cambridge, MA: MIT Press.

Simon, H.A. (1957). Models of Man. New York: John Wiley.

Simon, H.A. (1962). The Architecture of Complexity. Proceedings of the American Philosophical Society, 106 (6), 467-482.

Snowden, D.J., & Boone, M.E. (2007). A leader's framework for decision making. Harvard Business Review, November, 69-76.

Stradley, J., & Karraker, D. (2006). The electronic part supply chain and risks of counterfeit parts in defense applications. IEEE Transactions on Components and Packaging Technologies, 29 (3), 703-705.

Tang, C. S., & Zimmerman, J. D. (2009). Managing new product development and supply chain risks: The Boeing 787 case. Supply Chain Forum: International Journal, 10 (2), 74-86.

Tolk, A. (2003). The levels of conceptual interoperability model. Proceedings of the Fall Simulation Interoperability Workshop. Orlando, Florida, September.

Tolk, A. (Ed.).(2013). Ontology, Epistemology, and Teleology for Modeling and Simulation. Berlin Heidelberg: Springer-Verlag.

Trist, E., & Bamforth, W. (1951). Some social and psychological consequences of the long wall method of coal getting. Human Relations, 4, 3-38.

Ulrich, W. (1983). Critical Heuristics of Social Planning. Berlin: Haupt.

Ulrich, W. (1988). Systems Thinking, Systems Practice, and Practical Philosophy: A Program of Research. Systems Practice, 1 (2), 137-163.

Ulrich, W. (2003). Beyond Methodology Choice: Critical Systems Thinking As Critically Systemic Discourse. Journal of the Operational Research Society, 54, 325-342.

Weaver, W., & Shannon, C.E., (1963). The Mathematical Theory of Communication. Urbana, IL: University of Illinois Press.

Wiener, N. (1948, 1961). Cybernetics: Or Control and Communication in the Animal and the Machine. Cambridge, MA: MIT Press.

Zacharias, G,L., MacMillan, J., & Van Hemel, S.B. et al. (Eds.).(2008). Behavioral Modeling and Simulation. Washington, DC: National Academy Press.

Zeigler, B. P. (1990). Object-oriented simulation with hierarchical, modular models. Academic Press.

Zeigler, B.P., Praehofer, H., & Kim, T.G. (2000). Theory of Modeling and Simulation: Integrating Discrete Event and Continuous Complex Dynamic Systems. New York: Academic Press.